

Toward Environmental Sustainability in Mobile Internet Access: An Integrated Parametric Model for Radio Access Networks

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Declarations

I declare that this thesis results from my original research and that all conceptual, methodological, analytical, and interpretative work presented herein is entirely my own. I used DEEPL and CHATGPT as writing aids to improve the English phrasing of certain parts of the text, with their use limited to linguistic support.

I approached my research work with a background in electrical engineering, having graduated in 2021 from UCLouvain, Belgium. It builds on my Master's thesis *"Power consumption evaluation of mobile radio access networks using a bottom-up approach: modeling 4G networks and prospections of 5G deployment in Belgium"*.

I began my research work in 2021, at a time when the deployment of 5G in Belgium was the subject of significant public debate. This debate was shaped, among other factors, by growing awareness of the environmental and climate implications of digital technologies, particularly following the 2015 Paris Agreement and the 2018 IPCC Special Report on Global Warming of 1.5°C.

My understanding of these issues is informed by Ecological Economics and Political Ecology, fields that emphasize the strong sustainability perspective, sufficiency considerations, and post-growth thinking. These concepts shape the way I position my research questions and interpret the broader context, while the methods and results presented in this thesis adhere to established scientific standards.

My research work was funded by Proximus, a major telecommunications operator in Belgium. Proximus did not influence the formulation of the research questions, nor the methodology, analyses, or interpretation of the results. Through this collaboration, Proximus provided essential access to confidential data and information for model development and for grounding the research in operational realities.

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This thesis is the result of over four years of research conducted at UCLouvain between 2021 and 2026. It builds on the preliminary research I carried out for my master's thesis completed in 2021. Beyond my background in electrical engineering, pursuing a PhD has broadened my understanding of sustainability challenges and taught me how to incorporate these challenges into engineering practices. It has also prompted me to reflect on the role of engineers in transitioning society toward sustainability. While completing my PhD was highly rewarding on technical, scientific, and personal levels, it also required a fair amount of effort, commitment, and perseverance. None of this would have been possible without the help and support of many people, whom I would like to acknowledge.

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help, advice, and sometimes challenging feedback, from the beginning of my master's thesis to the end of my PhD. Many thanks as well to Robin and Youssef for our fruitful research collaborations and publications. Furthermore, I would like to acknowledge all the work (sometimes behind the scenes) of the administrative and technical staff of the ELEN department and of UCLouvain as a whole. Without them, it would not be possible to carry out qualitative research.

Alongside my thesis, I also had the opportunity to participate in various projects and initiatives aimed at discussing and rethinking the role of engineers in society, as well as reimagining related approaches and practices. These included involvement in the "Ingés en Transition" and "LCA in SST" initiatives, as well as the organization of the SICT doctoral school. To everyone I met there, I sincerely thank you for your kindness, open-mindedness, and willingness to think outside the box. I am also grateful for everything I learned through our various activities and lively discussions. Working with you in such a friendly and cooperative atmosphere was always a pleasure. Thank you also to my supervisors for allowing me to devote part of my time to these projects beyond my thesis work.

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Abstract

Digitalization increasingly affects human activities through information and communication technologies (ICTs). This transformation is often presented as a means of fostering sustainable human societies by improving quality of life while mitigating environmental impacts. Among ICT services, this thesis focuses on *mobile Internet access* provided by cellular radio access networks (RANs). RANs are typically operated by mobile network operators (MNOs) and comprise numerous base stations (BSs) deployed across a territory to provide coverage for mobile devices. These devices can be digital interfaces for human subscribers or connected objects. Mobile Internet access is currently provided by 4G and 5G RANs, while 6G is under development. Successive generations of mobile communications have led to a $\times 50$ increase in global mobile data traffic from 2014 to 2024. Meanwhile, electricity consumption and greenhouse gas (GHG) emissions from mobile networks have steadily increased. In 2020, these networks consumed 161 TWh of electricity and emitted 118 MtCO₂eq globally, primarily due to RAN operations.

In the context of climate change, the International Telecommunication Union (ITU) has set a GHG reduction target of -37% for mobile networks between 2020 and 2030, in line with the Paris Agreement. Meeting this target requires a rapid and strong transition to reverse the historical upward trend. Conventional engineering strategies for achieving this transition focus on improving network energy efficiency, under the assumption that absolute decoupling between GHG emissions and mobile data traffic is possible. However, historical data show that efficiency strategies alone have been insufficient to date, as rebound effects have offset the potential energy savings. Therefore, sufficiency strategies may be necessary for both the network deployment and network usage. At the same time, Internet access has become essential for fulfilling human needs in modern societies and is considered part of the decent living standards. Consequently, a substantial deterioration of mobile Internet access would be undesirable, although minimum quality of service (QoS) requirements remain debatable.

Achieving sustainability in mobile Internet access therefore requires meeting two constraints: (i) reducing its environmental impacts to remain within planetary

boundaries, and (ii) providing sufficient QoS to fulfill human needs. Adopting a strong sustainability perspective, this thesis considers environmental sustainability as a prerequisite for human well-being. Accordingly, the goal of the thesis is

to support the implementation of QoS-informed transition strategies for RANs toward environmental sustainability in mobile Internet access.

Specifically, the thesis aims to enable researchers, MNOs, and network equipment manufacturers to assess the techno-environmental performances of different RAN configurations, support the eco-design and optimization of next-generation BSs, and inform decision-making and strategic planning for sustainable RAN deployment strategies. To achieve this goal, the thesis is divided into two parts.

The first part of the thesis develops an integrated RAN model that simultaneously assesses QoS, energy consumption, and environmental impacts under given operating conditions. This model combines three parametric models for large-cell commercial BSs: (i) a communication performance model, (ii) a power consumption model, and (iii) a life-cycle environmental impact model. These models depend on multiple configuration variables and are calibrated using regression analysis of specific empirical data, including on-site measurements from MNOs, technical documentation from manufacturers, and teardowns of BS components.

The second part of the thesis leverages the integrated RAN model through two applications specific to Belgium. First, it evaluates the techno-environmental performances of different RAN configurations under typical operating conditions to identify efficient BS designs and effective power-saving strategies (PSSs). Second, it examines prospective scenarios for a range of RAN deployment strategies and different traffic demand trajectories from 2020 to 2030. The environmental sustainability of each scenario is then evaluated by comparing its cumulative GHG emissions with normative carbon budgets derived from an absolute perspective. These two applications thus illustrate how the integrated RAN model can inform network design and decision-making through strategic planning.

Results show that BS energy consumption scales primarily with the number of installed frequency bands and the transmit power per band. Under typical operating conditions, static power consumption dominates but can be reduced through PSSs. From a life-cycle perspective, the use stage dominates BS environmental impacts across all categories. Production stage impacts also contribute significantly to certain categories and scale similarly to energy consumption. In contrast, the distribution and end-of-life stages have negligible impacts. Thus, reducing BS energy consumption and opting for low-impact electricity sources are key mitigation levers. The prospective study further reveals that trajectories of QoS, energy consumption and GHG emissions are primarily driven by the RAN deployment strategy rather than by traffic demand. However, none of the examined deployment strategies achieves absolute decoupling. Only a post-growth strategy combined with a sufficiency-oriented demand meets the GHG reduction target of the ITU.

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- [JP3] L. Golard, R. Dethienne, J. Louveaux, and D. Bol, "A parametric life-cycle model for assessing environmental impacts of 4G and 5G cellular base stations," *The International Journal of Life Cycle Assessment*, vol. 31, art. 59, 2026. DOI: 10.1007/s11367-026-02597-1.

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- [CP1] T. Pirson, L. Golard, and D. Bol, "Evaluating the (ir)relevance of IoT solutions with respect to environmental limits based on LCA and backcasting studies," in *Ninth Computing within Limits*, 2023. DOI: 10.21428/bf6fb269.6af396ff.
- [CP2] L. Golard, Y. Agram, F. Rottenberg, F. Quitin, D. Bol, and J. Louveaux, "A parametric power model of multi-band sub-6 GHz cellular base stations using on-site measurements," in *IEEE 35th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2024. DOI: 10.1109/PIMRC59610.2024.10817448.

List of acronyms

2G-GSM	2nd Generation – Global System for Mobile Communications
3G-UMTS	3rd Generation – Universal Mobile Telecommunications System
3GPP	3rd Generation Partnership Project
4G-LTE	4th Generation – Long Term Evolution
5G-NR	5th Generation – New Radio
AAU	Active Antenna Unit
ABF	Adaptive Beamforming
AC	Alternating Current
ACS	Active Cooling System
ADP	Abiotic Resource Depletion Potential
AE	Antenna Element
AESA	Absolute Environmental Sustainability Assessment
AFE	Analog Front End
AI	Artificial Intelligence
ALCA	Attributional Life Cycle Assessment
APT	Average Power Tracking
AS	Amplification Stage
ASR	Absolute Sustainability Ratio
AU	Antenna Unit
BBU	Baseband Unit
BLER	Block Error Rate
BS	Base Station
CAGR	Compound Annual Growth Rate
CDF	Cumulative Density Function
CLCA	Consequential Life Cycle Assessment
CW	Continuous Waveform
DBB	Digital Baseband
DC	Direct Current

DL	Downlink
DTX	Discontinuous Transmission
E&M	Entertainment and Media
E³F	Energy Efficiency Evaluation Framework
EF	Environmental Footprint
EoL	End-of-Life
ET	Envelope Tracking
ETSI	European Telecommunications Standards Institute
EU	European Union
FCE	Final Consumption Expenditure
FDD	Frequency Division Duplex
FFI	Fossil Fuels and Industry
FPI	Foreground Process Inventory
FR1	Frequency Range 1
FU	Functional Unit
GaAs	Gallium Arsenide
GaN	Gallium Nitride
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GSD	Geometric Standard Deviation
GVA	Gross Value Added
GWP	Global Warming Potential
H2H	Human-to-Human
HPBW	Half Power Beamwidth
IAF	Impact Assessment Factor
IC	Integrated Circuit
ICIC	Inter-Cell Interference Coordination
ICT	Information and Communication Technology
IoT	Internet of Things
IPBO	Input Power Back-Off
IPCC	Intergovernmental Panel on Climate Change
IQR	Inter-Quartile Range
ITU	International Telecommunication Union
LCA	Life Cycle Assessment
LCE	Life Cycle Engineering
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCM	Life Cycle Management
LDMOS	Laterally-Diffused Metal-Oxide Semiconductor
LULUCF	Land Use, Land-Use Change, and Forestry

M2M	Machine-to-Machine
MCS	Modulation and Coding Scheme
MIMO	Multiple-Input Multiple-Output
MNO	Mobile Network Operator
OFDM	Orthogonal Frequency-Division Multiplexing
OPBO	Output Power Back-Off
P1dB	1-dB Gain Compression Point
PA	Power Amplifier
PAPR	Peak-to-Average Power Ratio
PCB	Printed Circuit Board
PCBA	Printed Circuit Board Assembly
PDF	Probability Density Function
PRU	Physical Resource Unit
PSS	Power Saving Strategy
PSU	Power Supply Unit
PV	Photovoltaic
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RAN	Radio Access Network
RE	Resource Element
RF	Radio Frequency
RFU	Radio Frequency Unit
RRU	Remote Radio Unit
RU	Radio Unit
RX	Reception
SBTi	Science-Based Targets initiative
SCS	Subcarrier Spacing
SDG	Sustainable Development Goal
SE	Spectral Efficiency
SINR	Signal-to-Interference-plus-Noise Ratio
SOS	Safe Operating Space
SoSOS	Share of the Safe Operating Space
SSP	Shared Socio-economic Pathway
TDD	Time Division Duplex
TRX	Transceiver
TX	Transmission
UE	User Equipment
UL	Uplink
UN	United Nations
UPS	Uninterruptible Power Supply

1

Introduction

Digitalization increasingly affects human activities, including energy production and distribution, transportation and logistics, industrial manufacturing, agriculture, entertainment and media, etc. This transformation is often presented as a means of fostering sustainable human societies by improving quality of life while mitigating environmental impacts [1–4]. Digitalization is driven by innovations and developments in information and communication technologies (ICTs), which enable access to and processing of information, as well as human-to-human (H2H) and machine-to-machine (M2M) communications [5]. As illustrated in Figure 1.1, the ICT sector is traditionally divided into three subsectors: (i) end-user devices (e.g., laptops and smartphones), (ii) communication networks (e.g., fixed and mobile access networks), and (iii) data centers (e.g., cloud and enterprise servers) [6, 7]. Yet, the advent of Internet of things (IoT) and artificial intelligence (AI) is reshaping the structure of the ICT sector [8–10], making digital technologies ubiquitous and blurring its boundaries with other economic sectors [JP2].

Internet access is one of the key functions enabled by ICTs. It can be provided by fixed and mobile networks, as well as emerging non-terrestrial networks [6, 11]. This thesis specifically focuses on *mobile Internet access* provided by cellular radio access networks (RANs). As shown in Figure 1.1, RANs transmit and receive radio frequency (RF) signals to and from mobile devices to establish communication with the mobile core network [12–14]. Mobile devices are usually referred to as user equipment (UE), which can be digital interfaces for human subscribers or connected objects. A RAN is typically operated by a mobile network operator (MNO) and comprises numerous base stations (BSs) deployed across a territory to provide coverage to UEs. The characteristics of wireless communication services provided by a RAN depend on the technology and configuration of its constituent BSs. Mo-

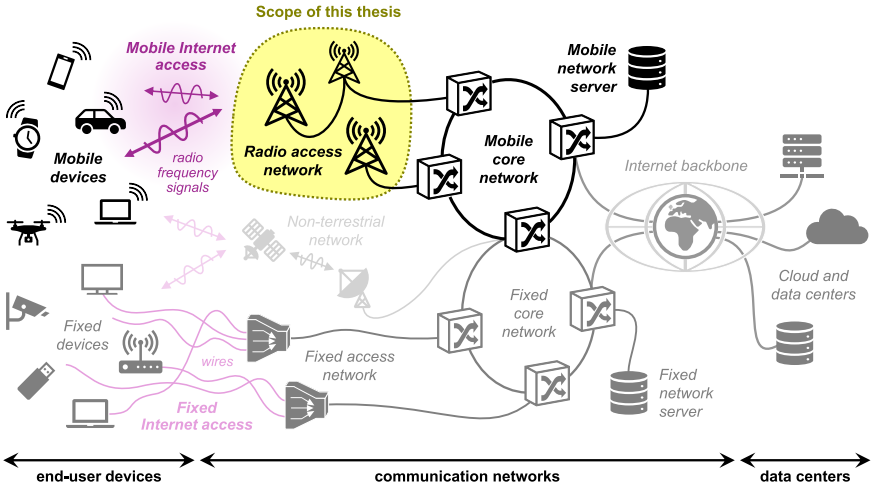


Fig. 1.1 Scope of the thesis in relation to the sector of information and communication technologies, which traditionally includes end-user devices, communication networks, and data centers. This representation is illustrative, as this sector continuously evolves with technological advances, and its boundaries depend on the chosen inclusion criteria. This thesis focuses on mobile Internet access provided by cellular radio access networks, which connect mobile devices to the mobile core network via radio frequency signals.

mobile Internet access emerged with 3G – Universal Mobile Telecommunications System (3G-UMTS) in the 2000s, but it offered limited data throughput. This limitation prompted the rollout of 4G – Long Term Evolution (4G-LTE) in the 2010s to provide true mobile broadband Internet access [12–14]. Subsequently, 5G – New Radio (5G-NR) became commercially available in the early 2020s, with performance targets including a user experienced data throughput of 100 Mbps/UE, latency of 1 ms, and connection density of 10^6 UE/km² [15]. While the rollout of 5G-NR is still ongoing, the development and standardization of 6G have begun, with commercial launch projected around 2030 [11, 16, 17].

The successive technological developments in mobile communications have supported the rapid increase in global mobile data traffic, as shown in Figure 1.2(a). With a compound annual growth rate (CAGR) of +48%/year between 2014 and 2024, the growth in mobile data traffic volume has outpaced the growth in fixed data traffic volume, accounting for nearly 20% of the total data traffic volume in 2024 compared to only 6% in 2014 [18, 19]. The rise in mobile data traffic is mainly due to two factors. First, the number of mobile Internet subscriptions increased from 37 to 95 per 100 people worldwide, surpassing the 20 fixed Internet subscriptions per 100 people in 2024 [19]. Second, the average mobile data volume per subscription increased from approximately 1 GB/month in 2014 to 16 GB/month

in 2024. Alongside this growth in mobile data traffic, MNOs continuously expand the capacity of their networks to improve quality of service (QoS), e.g., by increasing the total available bandwidth of existing BSs with additional higher frequency carriers, refarming low frequency carriers from legacy to more recent communication protocols, using advanced multiple-input multiple-output (MIMO) techniques, and deploying new BSs to densify the RAN [20–24].

Meanwhile, greenhouse gas (GHG) emissions from communication networks have steadily increased, as shown in Figure 1.2(b). According to bottom-up assessments by Malmmodin et al. [25–27], these GHG emissions rose by +27% from 144 MtCO₂eq in 2010 to 183 MtCO₂eq in 2020. The World Bank [28] used a similar approach to estimate the carbon footprint of telecommunications operators at 166 MtCO₂eq in 2022. Using a top-down approach, the Exiobase [29] estimates that the "Post and Telecommunications" emitted 194 MtCO₂eq in 2010 and 240 MtCO₂eq in 2020, reflecting an upward trend consistent with bottom-up assessments¹. The breakdown by network type indicates that emissions from fixed networks decreased from 2007 to 2020, whereas emissions from mobile networks roughly doubled, reaching 118 MtCO₂eq in 2020, or 64% of total emissions from both network types [27]. Bottom-up studies [25–28, 30] further indicate that about 80% of total GHG emissions from networks are due to operational electricity consumption, while the remainder corresponds to embodied emissions. Focusing on mobile networks, the total electricity consumption in 2020 is estimated at 161 TWh worldwide, most of which is attributable to RANs [27, 30, 31].

A comparison of Figures 1.2(a) and 1.2(b) reveals that mobile networks have a higher carbon intensity per unit of data traffic than fixed networks. In contrast, the carbon intensity per Internet subscription is lower for mobile networks than for fixed networks. However, the QoS provided by mobile and fixed networks is not directly comparable, as it differs in terms of data throughput, coverage, connection robustness, and other service characteristics. Pricing policies adopted by MNOs also differ between the two network types [32]. Yet, it is important to note that the assessment results in Figure 1.2(b) encompass all communication technologies, including 2G – Global System for Mobile Communications (2G-GSM), which does not provide Internet access, while Figure 1.2(a) depicts Internet-related data only.

1.1 The sustainability challenge in mobile Internet access

In the context of climate change, the Paris Agreement sets the goal of limiting the increase in global average temperature to “well below 2°C above pre-industrial levels” [33]. In relation to this global challenge, mobile networks in 2020 accounted for approximately 0.2% of global GHG emissions [4] and 0.6% of global electricity consumption [34]. Although these percentages are small, this sector must also

¹The difference of ~ 50 MtCO₂eq between bottom-up and top-down assessments is mainly attributed to scope discrepancies, e.g., the inclusion of postal services in Exiobase estimates.

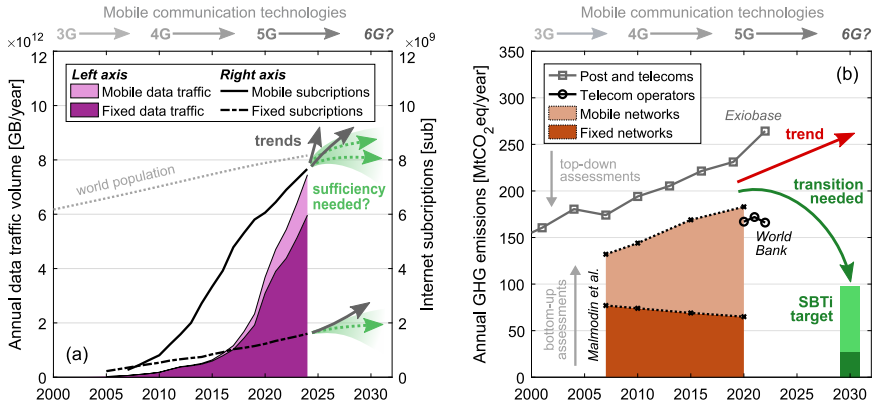


Fig. 1.2 Historical trends for fixed and mobile networks: (a) annual data traffic volume and Internet subscriptions, and (b) annual greenhouse gas (GHG) emissions. Mobile network usage and GHG emissions increase with successive technological developments. To achieve the 2030 SBTi target, a transition is necessary, raising the question of whether sufficiency strategies are needed in addition to efficiency strategies (data in (a) from [18, 19], and in (b) from Malmudin et al. [25–27], World Bank [28], and Exiobase [29]).

contribute to *decarbonization*, as must every other sector of the economy [4]. Following the approach of the Science-Based Targets initiative (SBTi), the International Telecommunication Union (ITU) has set a GHG reduction target of -37% for mobile networks between 2020 and 2030 [35]. At the global level, this corresponds to 70 MtCO₂eq in 2030, which is compatible with 171 TWh of electricity consumption if the average carbon intensity of electricity decreases by -67% over 2020–2030 [35]. Yet, historical trends indicate that the global carbon footprint and electricity consumption of mobile networks are on the rise. Prospective studies at the country level such as [JP1] and [36–38] also predict that these trends are likely to continue in the future. These findings indicate that achieving the SBTi target requires a rapid and strong transition, as depicted in Figure 1.2(b). A comprehensive perspective on *environmental sustainability* should also include categories of environmental impacts beyond climate change, as indicated by the Planetary Boundaries framework [39–42]. However, quantified targets in these additional impact categories are yet to be established for communications networks.

Besides reducing the carbon intensity of electricity, conventional engineering strategies for achieving environmental sustainability in mobile Internet access focus on improving the network energy *efficiency* [11, 15]. Accordingly, modern BSs implement power saving strategies (PSSs), including deep sleep modes, lean carrier design, and dynamic antenna selection [43–46], BSs tend to be shared between MNOs to mutualize static power consumption [47], and RAN densification allows BSs to operate with lower RF output power [20–24]. However, efficiency strate-

gies alone may be insufficient to reduce the total energy consumption of mobile networks, as they can trigger rebound mechanisms, such as accelerating mobile Internet usage and increasing QoS expectations among subscribers. The resulting rebound effects thus partially or fully offset the expected energy savings [48–50]. For instance, 5G-NR targets aim for $\times 100$ the energy efficiency of 4G-LTE, but simultaneously $\times 100$ the data traffic capacity [15], which would result in a constant total energy consumption. In reality, relying solely on efficiency strategies implicitly assumes that *absolute decoupling* [51, 52] between GHG emissions and usage levels is possible in mobile networks. Historical trends, however, show that global GHG emissions from mobile networks have continued to increase over time despite engineering efforts to maximize spectral efficiency and transmit power efficiency [26, 53–55], thereby indicating *relative decoupling* only [51, 52]. These observations therefore call for a paradigm shift in the mobile network industry.

Ensuring an effective environmental transition might thus require *sufficiency* strategies in addition to efficiency strategies [4, 56–58]. On the supply side, sufficiency may affect the RAN deployment strategies and QoS objectives of MNOs, the design of next-generation BSs by manufacturers, the type and content of services offered on the Internet, etc. On the demand side, sufficiency relates to the behavior of private and enterprise subscribers through their QoS expectations, the type and content of Internet services they consume, the number of objects to which connectivity is added, etc. Together, sufficiency strategies on both sides could result in slower growth or even stabilization of mobile data traffic volume and the number of mobile Internet subscriptions, as illustrated in Figure 1.2(a). However, the extent of sufficiency necessary to achieve environmental sustainability remains unclear. At the same time, the human aspects of sustainability, which relate to society and the economy, should be considered alongside the environmental aspects, as emphasized by the Doughnut Economics framework [59, 60]. In modern societies, Internet access in particular has become essential for fulfilling human needs and is considered part of the decent living standards for human well-being [56, 61]. For this reason, Internet access is increasingly recognized as a new human right [62]. Therefore, a substantial deterioration of mobile Internet access would be undesirable and ultimately unsustainable, although minimum QoS requirements remain debatable and not clearly defined.

1.2 Goal of the thesis and research questions

Achieving sustainability in mobile Internet access requires meeting two constraints: (i) reducing its environmental impacts to remain within planetary boundaries, and (ii) providing sufficient QoS to fulfill human needs. Adopting a *strong* sustainability perspective [63–65], this thesis treats the preservation of ecological system integrity as a prerequisite for human well-being [39–42]. Therefore, it focuses on

environmental sustainability. Accordingly, the **goal** of this thesis is

to support the implementation of QoS-informed transition strategies for RANs toward environmental sustainability in mobile Internet access.

Specifically, this thesis aims to enable researchers, MNOs, and network equipment manufacturers to assess and compare the techno-environmental performances of different RAN configurations at the country level, support the eco-design and optimization of next-generation BSs, and inform decision-making and strategic planning toward sustainable RAN deployment strategies. More broadly, this thesis seeks to illustrate how environmental sustainability can be systematically incorporated into engineering research.

This thesis thus focuses on RANs and, in particular, on the communication-specific components of BSs that provide mobile Internet access. Conversely, it excludes the mobile core network, Internet backbone, data centers, and UEs, as well as emerging non-terrestrial networks (see Figure 1.1). Adopting a life-cycle perspective, the thesis focuses on direct environmental impacts [66–69]. To capture direct substitution, optimization, and rebound effects within RAN boundaries, this thesis generally assesses environmental impacts in absolute terms rather than through relative efficiency metrics. However, the indirect effects enabled by mobile Internet access in other sectors, such as indirect optimization, substitution, and rebound effects, as well as behavioral and structural effects at the macro level [66–69], are outside the scope of this thesis. Accordingly, this thesis does not examine the indirect (positive and negative) impacts of RANs, such as GHG abatement potential or induced increases in energy demand [1–3]. Nevertheless, this thesis may serve as a basis for future works investigating both the direct (first-order) and indirect (higher-order) effects of digitalization and ICTs [70–72].

To achieve the goal of the thesis, three **research questions** are formulated.

- RQ1** *How can a RAN be modeled to simultaneously assess its QoS and direct environmental impacts under given operating conditions?*
- RQ2** *What BS designs are efficient in terms of QoS and direct environmental impacts under typical operating conditions?*
- RQ3** *What RAN deployment strategy should be adopted by MNOs to transition toward environmental sustainability from an absolute perspective?*

To address **RQ1**, this thesis develops an integrated parametric model for RAN that simultaneously assesses its QoS, energy consumption, and life-cycle environmental impacts. Specifically, the entire BS life cycle is modeled using the life cycle assessment (LCA) methodology [73] across multiple environmental impact indicators. At the time of writing this thesis, the proposed RAN model is planned to be published as an open-source software tool. Then, **RQ2** is addressed by applying the integrated RAN model to assess BSs under typical operating conditions. The objective

here is not to optimize BS designs directly, but rather to provide recommendations for more efficient designs and to identify areas for optimization in future works. Finally, **RQ3** is addressed through a prospective country-level study applying the integrated RAN model to identify transition strategies for mobile networks toward environmental sustainability. This thesis specifically explores RAN deployment strategies in Belgium from 2020 to 2030, supported by the absolute environmental sustainability assessment (AESA) methodology [74–76].

1.3 Outline of the thesis

Following this introductory chapter, two chapters establish the research background for this thesis and lay the foundation for addressing the three research questions. These chapters aim to situate and motivate the specific contributions of the thesis in relation to existing literature and scientific knowledge.

Chapter 2 reviews the frameworks and methods that support the operationalization of environmental sustainability in engineering practices. Thus, it establishes the conceptual and methodological foundation for the rest of the thesis. The chapter first outlines the key aspects of sustainability, with a focus on environmental sustainability. Then, it covers the operationalization of life-cycle thinking in engineering practices through life cycle engineering (LCE) and introduces the complementary assessment methodologies of LCA and AESA. Finally, it presents techniques from futures studies that enable prospective planning of transition strategies toward environmental sustainability, with a focus on backcasting. This chapter builds upon the considerations outlined in [CP1].

Chapter 3 reviews the state of the art on RAN models and assessments, thereby establishing the scientific foundation for the development and application of the integrated RAN model in the rest of the thesis. The chapter first reviews the literature on environmental impact assessments of mobile networks, focusing exclusively on direct (first-order) impacts. Then, it reviews the literature on models for QoS, energy consumption, and life-cycle environmental impacts of RANs, including integrated network models and simulators, as well as specific BS models. Finally, it summarizes the main research gaps in the existing literature and relates these gaps to the three research questions. This chapter builds upon literature reviews performed in [JP1], [CP2], and [JP3], as well as insights from [JP2].

The rest of the thesis follows the structured LCE approach proposed by Hauschild et al. [63, 77]. As detailed in Chapter 2, this approach operationalizes absolute environmental sustainability in engineering practices by integrating both bottom-up LCA and top-down AESA methodologies. Figure 1.3 shows how LCE is applied in this thesis. The RAN is considered a means of fulfilling human needs by providing mobile Internet access within the ICT sector. Additionally, climate change is the primary focus among the planetary boundaries, and the associated

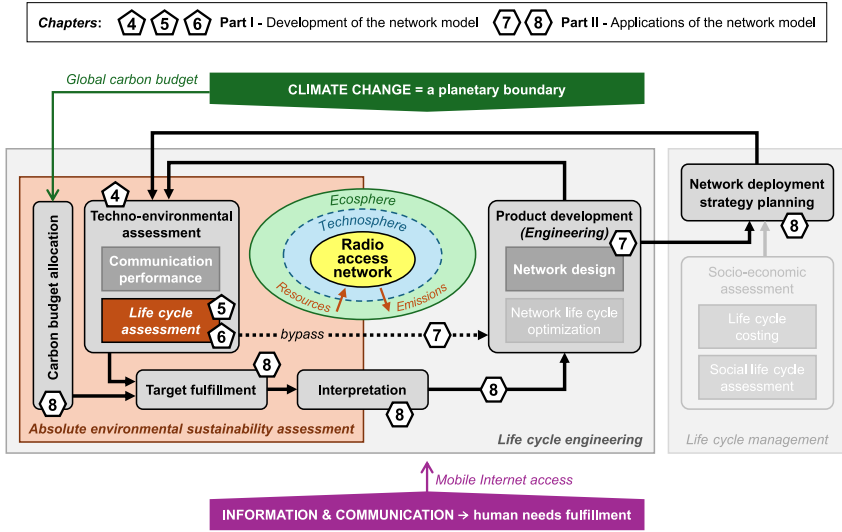


Fig. 1.3 General research approach of this thesis following the life cycle engineering approach proposed by Hauschild et al. [63, 77] and detailed in Chapter 2. The radio access network is a means of fulfilling human needs by providing mobile Internet access. The primary focus among the planetary boundaries is climate change, associated with a global carbon budget. Chapters of Part I and Part II are outlined as part of this approach.

global carbon budget represents the absolute environmental constraint. Figure 1.3 also indicates how subsequent chapters of the thesis relate to the LCE approach. Specifically, these chapters are organized into two parts.

By developing an integrated parametric model for RANs, **Part I** addresses **RQ1** in Chapters 4, 5 and 6. Within the LCE approach, this model enables the techno-environmental assessment of the RAN. Building upon state-of-the-art models, this part of the thesis presents the models for assessing the energy consumption and life-cycle environmental impacts of RANs. However, the thesis does not present the communication performance model because it is not considered a novel contribution compared to state-of-the-art models.

Chapter 4 introduces the overall methodology for developing the integrated RAN model designed to simultaneously assess the QoS, energy consumption, and life-cycle environmental impacts. The chapter first defines the general goal and scope of the model. Then, it presents the general modeling approach and provides an overview of the model. Unlike [JP1], the integrated RAN model separates the modeling of QoS and energy consumption, thereby enabling greater flexibility and an explicit physics-based representation of RANs and its constituent BSs. The model is also structured across multiple time scales, combining short-term QoS as-

assessment with long-term life-cycle impact assessment. Next, the chapter proposes an approach for estimating the technological model parameters based on empirical data and quantifying the associated uncertainties. Finally, it defines the set of typical BS configurations used in the following chapters to generate illustrative results and to validate the proposed models against independent observations. This chapter combines and extends the methodologies introduced in [CP2] and [JP3].

Chapter 5 develops a parametric model for assessing the power consumption of commercial BS architectures. This model is designed to be integrated within the parametric RAN model and follows the methodology introduced in Chapter 4. The chapter begins with a refined goal and scope definition for the BS power model, followed by its specific modeling approach. Then, analytical power models are developed for different BS components based on variables such as the carrier frequency, bandwidth, transmit power, etc. Developed around multiple time scales, these models capture the nonlinear effects induced by sleep modes and PSSs. Additionally, realistic estimates for the technological model parameters are derived from specific empirical data, along with uncertainty quantification. Next, the chapter illustrates the practical use of the proposed power model by assessing five typical BS configurations across three operating modes. The model is also validated against independent observations. Finally, a discussion outlines the main contributions, limitations, and perspectives for future works. This chapter adapts and extends the BS power model introduced in [CP2].

Chapter 6 develops a parametric model for assessing the environmental impacts of commercial BS architectures. This model is designed to be integrated within the parametric RAN model and follows the methodology introduced in Chapter 4. The chapter begins with a refined goal and scope definition for the BS life-cycle model, followed by its specific modeling approach. Grounded in the LCA methodology, the model encompasses multiple impact indicators and includes all life-cycle stages. The production stage is the primary focus of this chapter, whereas the use stage is modeled using the BS power consumption model developed in Chapter 5. For the foreground system, analytical life-cycle models are developed for different BS components based on variables such as the bandwidth, BS lifetime, electricity supply source, etc. For the background system, impact factors are calculated based on a LCA database. Realistic estimates for the technological model parameters are derived from specific empirical data, along with uncertainty quantification. Next, the chapter illustrates the practical use of the proposed life-cycle model by assessing five typical BS configurations. The model is also validated against independent observations. Finally, a discussion outlines the main contributions, limitations, and perspectives for future works. The content of this chapter is largely based on [JP3] and its supplementary material.

By applying the integrated RAN model developed in Part I, **Part II** addresses RQ2 in Chapter 7 and RQ3 in Chapter 8. Within the LCE approach, Chapter 7 by-

passes the AESA steps to evaluate different BS designs with a relative environmental perspective. Then, Chapter 8 applies AESA to evaluate different RAN deployment strategies and inform strategy planning toward environmental sustainability. The contents of these two chapters have not yet been published elsewhere.

Chapter 7 evaluates different BS designs under typical operating conditions. The examined BS designs are based on predetermined 4G-LTE and 5G-NR frequency bands, and the operating conditions capture both the network configuration and network usage. This chapter thus investigates how combinations of frequency bands affect the QoS, energy consumption, and environmental impacts of BSs, identifying key design trade-offs. However, rebound mechanisms and their associated rebound effects are not considered in this chapter, as the network usage is treated as an exogenous variable with respect to the provided QoS. The chapter begins with the definition of general use cases representative of RANs in Belgium, which serve as the basis for subsequent evaluations. Then, it analyzes the energy-saving potential of different PSSs. Based on this analysis, the chapter evaluates specific BS configurations supporting one or more frequency bands, and derives the corresponding energy intensity metrics using different normalization perspectives. Finally, the chapter discusses the main findings in light of the state of the art, identifies limitations, and outlines perspectives for future works.

Chapter 8 evaluates the absolute environmental sustainability of different RAN deployment strategies in Belgium from 2020 to 2030. Conducted as a prospective study, this chapter employs both forecasting and backcasting to develop scenarios. The chapter first defines a specific goal and scope for the study. Then, it constructs the scenarios representing a range of RAN deployment strategies (from business as usual to post-growth) under different network usage trajectories (including forecast, rebound, and sufficiency). Next, the chapter analyzes the resulting trajectories of QoS, energy consumption, and CO₂ emissions at the country level, and discusses the potential for absolute decoupling in RANs. Adopting an absolute perspective, it subsequently evaluates the environmental sustainability of each scenario with respect to the SBTi trajectory, as well as alternative carbon budgets determined based on different ethical norms. The evaluation perspective also briefly extends to social sustainability through the Doughnut Economics framework. Finally, the chapter discusses the main findings in light of the state of the art, identifies limitations, and outlines perspectives for future works.

The thesis concludes in **Chapter 9** by summarizing the main contributions and key findings in response to each research question. Additionally, it formulates practical recommendations for the stakeholders, including equipment manufacturers, MNOs, and mobile users. The conclusion also discusses the main limitations of the thesis and suggests perspectives for future research.

2

Frameworks and methods for environmental sustainability in engineering

This engineering-oriented thesis is largely framed by the concept of *environmental sustainability*. Accordingly, this chapter reviews the frameworks and methods that support the operationalization of this concept in engineering practices. This operationalization primarily involves life-cycle thinking and strategic planning. By examining the related frameworks and methods, this chapter establishes the conceptual and methodological foundation for the rest of the thesis.

This chapter first outlines the key aspects of sustainability in Section 2.1, with a focus on environmental sustainability. Then, Section 2.2 covers the operationalization of life-cycle thinking in engineering practices through LCE, and introduces the two complementary LCA and AESA methodologies. Finally, Section 2.3 presents techniques from futures studies that enable prospective planning of transition strategies toward environmental sustainability, with a focus on backcasting. This chapter builds upon the considerations outlined in [CP1].

2.1 Key aspects of sustainability

The concept of *sustainability* is central to this thesis as it guides the overall reasoning and puts the findings into perspective. This section presents the key aspects of sustainability, with a focus on environmental sustainability, and summarizes how the concept has evolved over time, particularly within the last 50 years.

2.1.1 A brief history of sustainability

Sustainability is rooted in economics, whose approach to resource use has evolved over time. As early as the late 18th century, Malthus postulated that the human population was growing faster than food production could support, which would inevitably lead to self-regulation of the population through poverty and famine [78]. Yet, during the 19th century, the economy underwent a radical transformation due to the widespread use of coal in industry and for domestic heating. Access to abundant fossil resources and subsequent technological progress greatly increased the Earth's carrying capacity, which (temporarily) refuted Malthus's thesis [57, 78]. Concurrently, Jevons observed that improvements in coal-use efficiency in steam engines did not lead to a decrease in coal consumption but rather a significant increase. This phenomenon, known as *Jevons paradox*, suggests that technological progress can unintentionally intensify resource use, rather than reduce it [79]. However, these concerns were soon overshadowed by growing confidence in market mechanisms and technological innovation, paving the way for the rise of neo-classical theories [78].

Concern about the depletion of the Earth's resources re-emerged in the second half of the 20th century, leading to the emergence of *ecological economics* [78], pioneered by Boulding [80] and Georgescu-Roegen [81]. These authors aimed to reintroduce the issue of natural resource use to economics, and to revise the disembodied conception of economic production [78]. According to this new school of thought, the economy operates as an anthropic ecosystem that transforms matter within a natural environment. Upstream, this system takes raw materials and transforms them into intermediate and finished products, which are then consumed by individuals and households. Both transformation and consumption lead to the production of waste and pollution, which is returned downstream to the natural environment. Waste and pollution can damage natural ecosystems if their discharge exceeds the environment's capacity to absorb them. Hence, the capacity of ecosystems to absorb pollution and waste can also be seen as a scarce resource. Moreover, Georgescu-Roegen argues that the economy has entropic limitations, and identifies *degrowth* as the solution to environmental problems, both in terms of resources and pollution [78, 81].

In the 1970's, Meadows and colleagues developed the first integrated computer model linking the economy and the environment, applying the principles of ecological economics [57, 78]. This model studied the evolution of the world's human population, food production, industrialization, pollution and consumption of non-renewable natural resources. Their goal was to analyze future scenarios to determine under which conditions the growth trajectories observed for these key parameters might be sustainable. Their findings, published in a report entitled "Limits to growth" [82], show that exponential economic and population growth is unsustainable in the long term in a world of finite resources, and will inevitably lead to crises and even collapse. Warning against unlimited growth, this report

left a lasting impression on public opinion and established ecological issues in the public debate for a long time to come. However, not all economists welcomed the report, resorting to the usual Malthusian criticisms. These more conventional economists, including Nordhaus, instead promoted technological innovation and the dematerialization of the economy as a solution to the limits to growth [78].

In 1987, the World Commission on Environment and Development of the United Nations (UN) published the report "Our Common Future" [83], which marked a turning point in the global understanding of sustainability. It introduced the widely cited definition of *sustainable development* as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs". This report was pioneering in explicitly recognizing that environmental limits exist, imposed by the state of technology, social organization, and the capacity of biosphere to absorb human impacts. Although these limits were acknowledged, they were not regarded as absolute constraints. Focusing on the fulfillment of human needs, the report reflects the belief in the potential of technological innovation and social change to foster a new era of economic growth compatible with sustainability.

Inspired by this definition of sustainable development, Elkington [84] introduced in 1997 the concept of the *triple bottom line* – people, planet, profit – to the business world. This concept states that a business is sustainable when it simultaneously pursues economic prosperity, environmental quality, and social justice. Since these three pillars are interrelated, interdependent, and partly in conflict, companies must strive to optimize their use of their economic, human and environmental capital [84]. The sustainability challenge is thus seen as a business opportunity for companies through technological innovation and improved eco-efficiency. At the same time, Goodland [85] rather emphasized the foundational role of the environment in sustainability and thus defined the *environmental sustainability* as the effort "to improve human welfare by protecting the sources of raw materials used for human needs and ensuring that the sinks for human wastes are not exceeded, in order to prevent harm to humans". This definition underlines the importance of environmental sustainability as the basis for social and economic sustainability.

In the 2000's, the *Anthropocene* was proposed as a new geological epoch characterized by the emergence of humanity as the dominant force driving global environmental change. This change has pushed the Earth system beyond the stable environmental conditions of the Holocene that enabled human civilizations to develop and thrive [39, 86]. To address the challenges of the Anthropocene, Rockström et al. [40] adopted the perspective of environmental sustainability to introduce the influential *Planetary Boundaries* framework (see Section 2.1.3.1). Based on this framework, Bjørn and Hauschild [87] introduced the *absolute environmental sustainability* into the field of product assessments. They suggested considering the planetary boundaries as a scarce resource that could be scaled down at the company or product level (see Section 2.2.2). This aligned with Rockström's call [88]

for a new paradigm in which the economy serves as a means to achieve social goals and generate prosperity within Earth system boundaries. This new paradigm would require coordinated efforts from nations, businesses, citizens, and institutions, integrated across all levels of policy-making.

In 2015, the UN adopted the "2030 Agenda for Sustainable Development" [89] aiming to end poverty, foster peaceful and just societies, protect the planet, ensure prosperity for all, and revitalize global partnerships. This agenda was specified through 17 sustainable development goals (SDGs) with associated targets for 2030. Among these, SDGs 13, 14 and 15 respectively target climate action, conservation and sustainable use of oceans and marine resources, and protection and sustainable use of terrestrial ecosystems and biodiversity. Additionally, SDG 12 addresses responsible consumption and production to promote sustainable patterns, while SDG 8 promotes sustained and sustainable economic growth, which is aligned with the long-term vision of the UN on sustainable development [83]. The simultaneous achievement of these SDGs implies the possibility of *green growth* that decouples economic growth from absolute environmental impacts. Yet, this prospect lacks empirical support on a large scale and is regarded as unlikely to happen in the future [51, 52]. Thus, echoing Georgescu-Roegen, contemporary ecological economists advocate complementing efficiency policies with *sufficiency* policies, shifting from growth to *post-growth* or *degrowth* paradigms [51, 90].

2.1.2 Weak versus strong sustainability

The concept of sustainability has evolved over time to encompass different, and sometimes conflicting, perspectives. While perspectives rooted in ecological economics emphasize limits to growth [82] and thermodynamic constraints [81], other perspectives highlight the potential of technological progress and economic growth to overcome environmental challenges [83]. These divergent perspectives can be categorized into two opposing visions of sustainability: *weak sustainability* and *strong sustainability* [63–65]. At the core of this divergence lies the issue of *substitutability* between the economy and the environment. This raises the question of whether we can replace “natural capital” with “human-made capital” without compromising sustainability in the long term.

Weak sustainability The weak sustainability perspective postulates the full substitutability of natural capital by manufactured capital [64, 65, 91]. Sustainability is thus ensured as long as the aggregate stock of capital – natural, human and economic – is maintained or increased over time and for future generations. This means that natural capital losses can be compensated, without restriction, by gains in other forms of capital, such as infrastructure, technology or knowledge. In this view, trade-offs and optimization between the three dimensions of sustainability are possible. The definitions of sustainable development [83] and SDGs [89] provided by the UN can thus be considered close to weak sustainability.

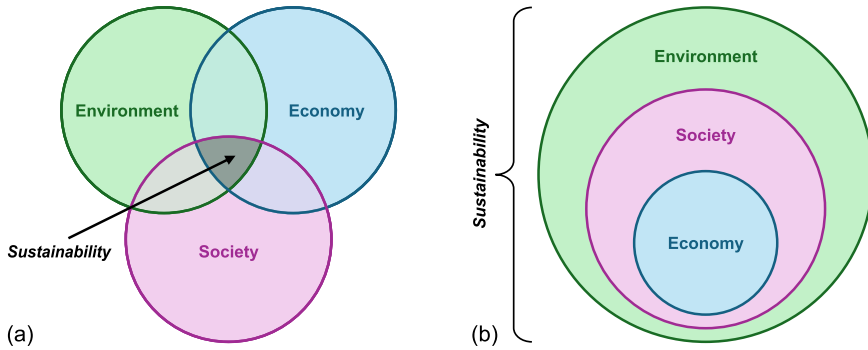


Fig. 2.1 Conceptual diagrams of the relationships between environment, society, and economy under (a) weak sustainability and (b) strong sustainability, illustrating the contrast between these two perspectives (adapted from [57]).

Strong sustainability The strong sustainability perspective, in contrast, holds that certain “critical” functions of the environment are irreplaceable in their contribution to human well-being [64, 65, 91]. This perspective emphasizes the need to maintain the integrity of ecological systems over time and for future generations. Manufactured capital can thus complement but not replace critical ecosystem services such as climate regulation, pollination, or protection from ultraviolet radiation. Therefore, it rejects the assumption of full substitutability between natural capital and human-made capital. Authors like Goodland [85], Rockström [88] and Hauschild [57] embrace the strong sustainability perspective and promote the concept of absolute environmental sustainability. Accordingly, they argue that certain environmental thresholds must not be exceeded, regardless of potential social or economic benefits.

The fundamental divergence between weak and strong sustainability is often illustrated as in Figure 2.1, where the diagrams represent the relationships between environmental, social and economic dimensions in the two sustainability perspectives. In Figure 2.1(a), weak sustainability is represented by three interlocking circles of equal importance, with sustainability located at their intersection. By contrast, strong sustainability is represented in Figure 2.1(b) by nested circles, the economy being embedded in society, itself embedded in the environment. These representations are not merely conceptual; they also raise normative issues [65]. On the one hand, how can we quantify the overall economic value of environmental (and social) capital? On the other hand, which environmental functions are critical and for whom, and what constitutes an intolerable loss? Addressing these questions requires inter-disciplinary approaches coupled with a broad societal debate.

2.1.3 Environmental aspects of sustainability

The environmental dimension of sustainability is given primary attention in this thesis. This focus aligns with the strong sustainability perspective and is further supported by the proximity of engineering to the environmental sciences, which facilitates the transfer of knowledge and methods between these fields. This section starts by presenting the Planetary Boundaries framework, and then further focuses on the issue of climate change.

2.1.3.1 Planetary Boundaries framework

First introduced in 2009, the Planetary Boundaries framework [39–41] proposes a science-based approach to environmental sustainability at the global scale. Grounded in the concept of the Anthropocene, it identifies nine *planetary boundaries* that define a “safe operating space” within which human societies can continue to develop and thrive with a low risk of destabilizing the Earth system. Transgressing one or more boundaries can trigger abrupt and potentially irreversible environmental changes, thereby jeopardizing the stable conditions of the Holocene that have supported human development. Although each boundary is defined separately, they are closely interconnected, and transgression of one can affect the stability of the others. Two of them – climate change and biosphere integrity – are recognized as “core” boundaries due to their fundamental importance for Earth system functioning [41].

Each planetary boundary is associated with one or more *control variables* (e.g., atmospheric CO₂ concentration) that capture the human pressure on a specific *Earth system process* (e.g., climate change). For each control variable, the framework distinguishes between a *threshold*, beyond which the Earth system may shift from the desired Holocene-like state to an undesired state, and a *boundary*, a human-determined value set at a “safe distance” from the threshold. This safe distance accounts for the scientific uncertainty about the precise location of the threshold and provides a time buffer for society to react before abrupt or high-risk environmental change occurs. Ultimately, defining boundaries involves normative judgments about how societies choose to deal with risk and uncertainty [39–41]. Figure 2.2(a) illustrates the relationship between control and response variables for a conceptual Earth system process. The locations of the boundary and threshold relative to the control variable determine the safe operating space (SOS), zone of increasing risk, and high-risk zone.

The latest update of the framework [42] refines the threshold and boundary estimates for each of the nine considered Earth system processes. As shown in Figure 2.2(b), six of the nine boundaries are currently transgressed, indicating that the Earth system is now well outside the SOS for humanity. The powerful messages communicated by this framework have attracted considerable attention to the concept of planetary boundaries from scientists and society, inspiring governance strategies and policies at all levels. Although planetary boundaries were not

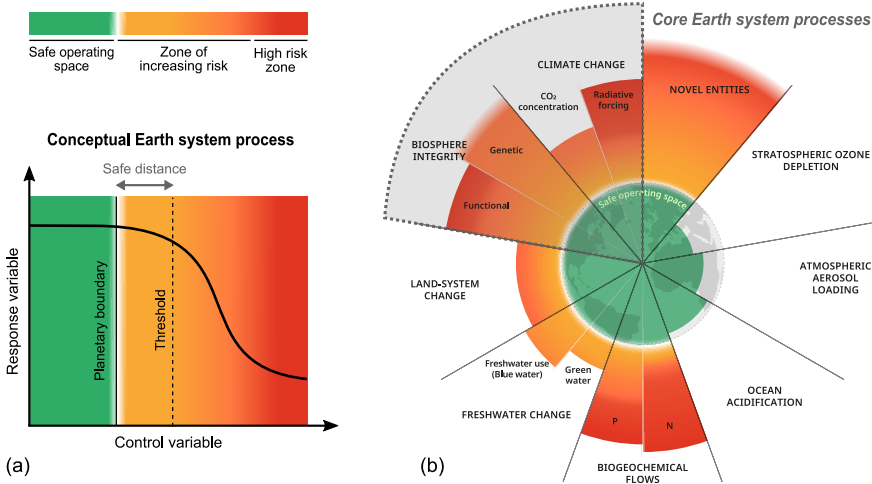


Fig. 2.2 Planetary Boundaries framework defining a safe operating space for humanity: (a) response variable versus control variable for a conceptual Earth system process and associated threshold and boundary, and (b) current status of control variables relative to all nine planetary boundaries (adapted from [41, 42]).

initially intended to be "down-scaled" to smaller levels, such as nations or companies, authors of the framework acknowledge the relevance of actions at all levels where policy-making occurs [41]. The framework also inspired governments and industries to adopt absolute targets for environmental sustainability and benchmark their activities accordingly [57].

2.1.3.2 Focus on climate change

According to the Planetary Boundaries framework [41], climate change is one of the two core processes of the Earth system. For this reason, climate change is the primary environmental focus of this thesis.

At the political level, climate change has become an important factor in governance and decision-making at both the international and national levels. In 1992, the Framework Convention on Climate Change of the UN committed its member states to negotiate ways to "prevent dangerous anthropogenic interference with the climate system". This led to the first major agreement on climate change mitigation in 1997: the Kyoto Protocol [92]. In 2015, the Paris Agreement [33] committed to limiting the increase in global average temperature to "well below 2°C above pre-industrial levels, and to pursue efforts to limit the temperature increase to 1.5°C in order to significantly reduce the risks and impacts of climate change". The pre-industrial baseline refers to the average global temperature between 1850 and 1900. To achieve this goal, the Paris Agreement recommends "achieving a bal-

ance between anthropogenic emissions by sources and removals by sinks of greenhouse gases in the second half of this century”, a state commonly described as “net zero” emissions. Similarly, the 2030 agenda of the UN [89] recognizes that “climate change is one of the greatest challenges of our time and that its adverse impacts undermine the ability of all countries to achieve sustainable development”.

At the scientific level, current knowledge on climate change is compiled in the reports of the Intergovernmental Panel on Climate Change (IPCC). In addition to providing a solid foundation for scientific research, these reports also serve to inform policy-making. The latest report is the “Sixth Assessment Report” consisting of three parts: “The Physical Science Basis” [93], “Impacts, Adaptation and Vulnerability” [94], and “Mitigation of Climate Change” [4]. It shows that climate change already affects all inhabited regions on Earth through increasingly frequent and severe weather and climate events, exposing human societies to significant vulnerabilities. It also shows that current global warming is entirely attributable to GHG emissions from human activities.

Currently, GHG emissions mainly consist of carbon dioxide (CO_2) from fossil fuels and industry (FFI) and land use, land-use change, and forestry (LULUCF), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (F-gases) [93]. These molecules have different global warming potentials (GWPs) and lifetimes in the atmosphere. For instance, the change in global surface temperature due to a pulse of CO_2 emissions remains relatively constant over time, while it decreases quickly with short-lived GHGs such as CH_4 . These differences result in distinct GWPs for each GHG, expressed in CO_2 equivalent unit (CO_2eq) relative to the GWP of CO_2 . However, long-term global warming is primarily determined by the cumulative emissions of CO_2 (from FFI+LULUCF) over time, rather than the annual GHG emissions. Figure 2.3 shows that the relationship between cumulative CO_2 emissions and global warming is nearly linear. This cumulative effect makes mitigating climate change an even greater challenge.

Accordingly, the IPCC proposes the concept of *remaining carbon budget* to describe the total net amount of CO_2 that could be released in the future (typically from 2020) by human activities while keeping global warming to a specific level [93]. Their most likely remaining carbon budget estimates are 500 and 1350 GtCO_2 for $+1.5^\circ\text{C}$ and $+2^\circ\text{C}$, respectively. Global warming projections are depicted in Figure 2.3 for a set of five illustrative scenarios corresponding to specific carbon budgets. A scenario is a description of how the future may develop, based on coherent and internally consistent assumptions. Scenarios are not predictions; instead, they provide a “what-if” investigation of the implications of various developments and actions.

The set of illustrative scenarios used by the IPCC is built on the Shared Socio-economic Pathways (SSPs), which provide narratives regarding gross domestic product (GDP), population, urbanization, economic collaboration, and human

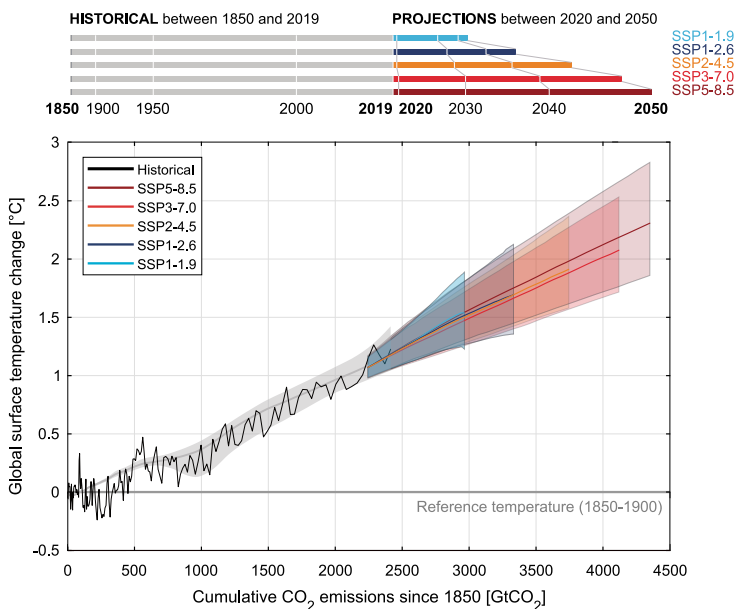


Fig. 2.3 Historical and projected near-linear relationship between cumulative CO₂ emissions (fossil fuels and industry + land use, land-use change, and forestry) and the increase in global surface temperature. For each of the five illustrative Shared Socio-economic Pathway (SSP) scenarios, the central line represents the median estimate, and the shaded area represents the very likely range (adapted from [93]).

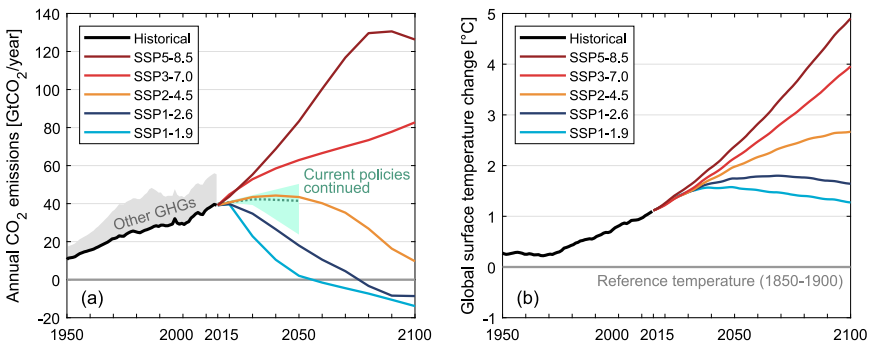


Fig. 2.4 Historical and projected climate change indicators for five illustrative Shared Socio-economic Pathway (SSP) scenarios: (a) annual CO₂ emissions (fossil fuels and industry + land use, land-use change, and forestry) on top of which historical emissions of other greenhouse gases (GHGs) are indicated in CO₂ equivalent unit, and (b) global surface temperature change relative to 1850–1900. Continuing current policies will result in +2.8°C by 2100 (adapted from [93, 95], data from [96–98]).

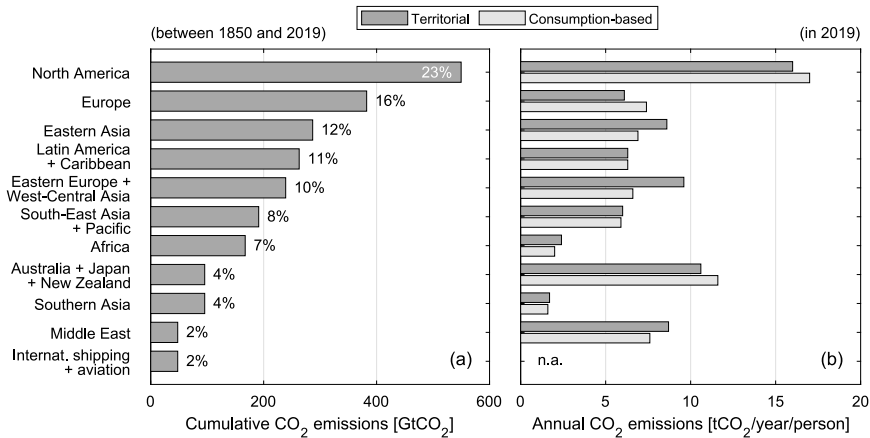


Fig. 2.5 Uneven distribution of CO₂ emissions (fossil fuels and industry + land use, land-use change, and forestry) per global region: (a) cumulative territorial CO₂ emissions between 1850 and 2019, and (b) annual territorial vs. consumption-based CO₂ emissions per person in 2019 (adapted from [4]).

and technological development [93]. Broadly, the SSPs represent “sustainability” (SSP1), a “middle-of-the-road” path (SSP2), “regional rivalry” (SSP3), “inequality” (SSP4), and “fossil fuel-intensive” development (SSP5). Then, a scenario SSPX-Y considers the SSP family X in which the radiative forcing Y is reached by 2100. The five illustrative scenarios (from SSP1-1.9 to SSP5-8.5) cover a wide range of plausible futures from below +1.5°C to over +4°C warming by 2100. Note that the SSP4 family (i.e., “inequality”) is excluded from the set of scenarios.

Figure 2.4 shows projections of net anthropogenic CO₂ emissions and corresponding global warming for the set of illustrative scenarios. This clearly shows the delay in global warming response to annual emissions. The target scenario for achieving the Paris Agreement is primarily SSP1-1.9, and ultimately SSP1-2.6. Both scenarios require a rapid and significant reduction in annual global emissions. They also assume net negative emissions in the second half of the century, meaning that human activities will have to remove more CO₂ from the atmosphere than they emit. However, the current national policies are not aligned with these trajectories, and are rather on track for +2.8°C by the end of the century [95].

Furthermore, regional contributions to global GHG emissions are distributed unevenly, both currently and cumulatively since 1850 [4]. As shown in Figure 2.5(a), around 40% of global cumulative CO₂ emissions are due to North America and Europe, whereas Africa accounts for only 7% (according to a territorial accounting). Moreover, Figure 2.5(b) shows that annual territorial emissions per person ranged from < 3 tCO₂ in Africa and Southern Asia to

> 15 tCO₂ in North America in 2019. These disparities reflect the different stages of development of these regions. Figure 2.5(b) also compares annual territorial and consumption-based CO₂ emissions per person. Consumption-based accounting is a method of considering the emissions associated with international trade throughout the entire supply chain necessary to fulfill the final demand for goods and services. For instance, it shows that Europe has relocated part of its consumption-related emissions abroad, while Eastern Asia emits more CO₂ within its territory than its consumption patterns require. These points indicate that countries are not equally responsible for global warming. Furthermore, their degree of responsibility may be perceived differently depending on the time frame and accounting method used.

2.1.4 Human aspects of sustainability

The human aspects of sustainability may seem more distant from the core of engineering practices. Although not central to this thesis, they remain essential to consider in the broader sustainability context.

The societal conditions for achieving sustainability involve ensuring that all people have access to the essential resources necessary for their *well-being*, including food, water, healthcare, energy and education [59, 89]. For the world's poorest population, this first means escaping poverty. At the same time, human activities must remain within a SOS for the Earth system. For the world's richest population, this raises questions about the long-term viability of their high living standards. In addition, human and environmental aspects are closely interdependent: environmental degradation can exacerbate poverty, while poverty can accelerate the unsustainable use of natural resources. Tackling one aspect without the other could result in failure on both fronts. Therefore, the major challenge of sustainability is to eradicate poverty and satisfy basic human needs while respecting absolute environmental thresholds.

The *Doughnut Economics*, proposed by Raworth [59, 60], is arguably the most influential framework for illustrating the sustainability challenge. Drawing on the Planetary Boundaries framework (see Section 2.1.3.1), it defines a "safe and just space for humanity" by combining the complementary concepts of planetary boundaries and social boundaries. As shown in Figure 2.6, the *ecological ceiling* forms an outer boundary, beyond which are risks of large-scale environmental degradation, while the *social foundation* forms an inner boundary, below which are many dimensions of human deprivation. Between the two boundaries lies an area – shaped as a doughnut – that represents an environmentally safe and socially just space for humanity to thrive in.

Raworth proposes to define the ecological ceiling using the Planetary Boundaries framework and to define the social foundation based on the SDGs, ranging from food and health to gender equality and peace and justice. Yet, this formula-

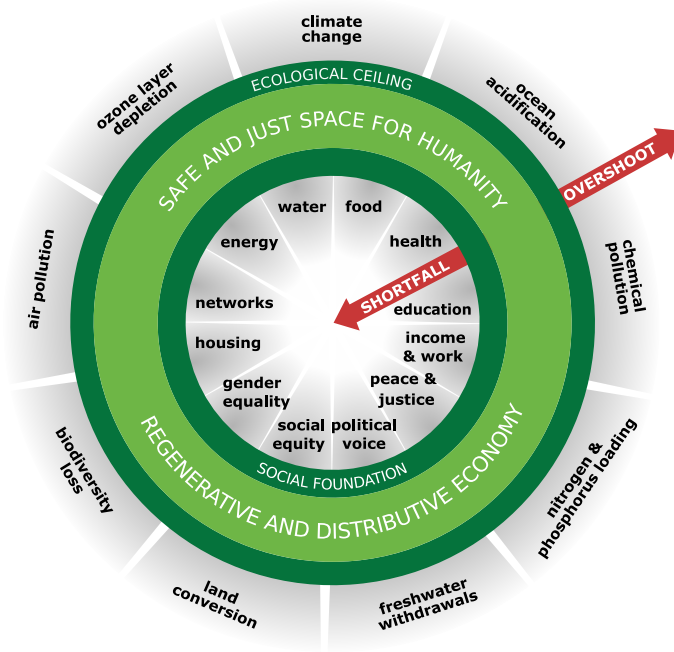


Fig. 2.6 Doughnut Economics framework defining a safe and just space for humanity located between the social foundation and the ecological ceiling (adapted from [60]).

tion of social foundation is debated, and other approaches advocate for the use of *human needs* theories [57]. The doughnut area is also considered as the space in which inclusive and sustainable economic development can take place. However, Raworth does not identify economic growth as a specific goal (at the global level), deeming it unrelated to the primary goals of Earth system stability and human well-being. The Doughnut Economics thus provides a visual and policy-relevant synthesis of the sustainability challenge, where social justice and environmental integrity are jointly necessary for human well-being. According to the framework, humanity is currently overshooting the ecological ceiling while millions of people fall short of meeting their basic needs [59, 60].

The existence of absolute planetary boundaries poses an additional ethical challenge: since further biophysical expansion is no longer a viable option, ensuring *fairness* in access to natural resources and environment's capacity to absorb pollution is crucial [57]. For instance, how should the necessary efforts to mitigate climate change be distributed among countries? Specifically, how should the rights to emit GHGs be allocated between countries or people, and according to which ethical principle? Section 2.2.4 presents one approach to addressing this challenge.

2.2 Operationalization of environmental sustainability in engineering

Engineering plays an important role in addressing societal challenges by providing technical solutions to perceived problems. Nowadays, however, the discipline must align its practices and innovations with global sustainability agendas, such as the Paris Agreement and the SDGs [99]. Therefore, operationalizing environmental sustainability in engineering requires robust frameworks and methods for assessing and minimizing the environmental impacts associated with technological innovations and related products. This section begins by outlining the main drivers of absolute environmental impacts according to the IPAT equation. Then, it introduces the principles of LCE, a sustainability-oriented engineering approach on which the research approach of this thesis is based. Finally, it presents two key assessment methodologies of LCE, namely the LCA and AESA. These methodologies are complementary: LCA is a bottom-up assessment methodology with a relative environmental perspective, while AESA is a top-down assessment methodology with an absolute environmental perspective.

2.2.1 Main drivers of absolute environmental impacts

The main drivers of absolute environmental impacts from human activities are usually expressed using the *IPAT equation* [57, 63] as

$$I = P \cdot A \cdot T. \quad (2.1)$$

This equation decomposes the total absolute environmental impact I as the product of three factors: the human population P , the human affluence A , and the technology factor T . Affluence represents the individual material living standard expressed in provided functionality or created value per person (e.g., \$/person), and the technology factor is the environmental intensity of the technology expressed as the relative environmental impact per provided functionality or created value (e.g., kgCO₂/\$). Accordingly, when population and affluence increase, the environmental intensity of technology must be reduced proportionally to prevent an increase in total environmental impact. In general, focusing on improving technological efficiency alone (i.e., reducing the factor T) is insufficient to ensure absolute environmental sustainability. Instead, policies that combine efficiency with limits on total consumption, namely sufficiency policies, should be implemented [57, 63]. However, the IPAT equation is a highly simplified representation of reality that does not capture the full complexity of societal and technological systems.

The IPAT equation can be used with a wide range of socio-economic and environmental indicators. For example, Appendix A.1 provides an IPAT-like decomposition of CO₂ emissions based on the GDP adjusted for purchasing power parity

and inflation worldwide, in the European Union (EU), and in Belgium. This shows that the affluence is the main driver of the global rise in CO₂ emissions, along with population growth, while decarbonization partly offsets the overall increase. The study of the “Great Acceleration” by Steffen [100] can also be used to compare the acceleration of many Earth system trends like ocean acidification, tropical forest loss or terrestrial biosphere degradation, with socio-economic trends like growth in the urban population, primary energy use, or international tourism. Furthermore, the IPAT equation can be applied to smaller scales, e.g., an economic sector or a product market, although this perspective is no longer strictly absolute. In that case, I represents the environmental impact of the entire product market, P the consumers of the product, A the amount of product per consumer, and T the environmental impact per product. Bol et al. [55] present such decomposition for the energy and carbon footprints of three ICT sub-sectors (i.e., semiconductor manufacturing, mobile Internet access, and data center usage).

In reality, the IPAT factors are interdependent, especially A and T [57, 63]. Thus, an increase in technological efficiency may drive an increase in affluence, which can result in an increase in absolute environmental impact. This phenomenon is known as the *rebound effect* [48–50], reminiscent of the Jevons paradox [79]. Initially focused on energy use, the rebound effect is commonly defined as the portion of potential energy savings lost due to the increased consumption, expressed as a ratio of the predicted efficiency improvement. For a given techno-economic activity, the rebound effect is calculated as

$$R = \frac{E_2(X_2) - E_2(X_1)}{E_1(X_1) - E_2(X_1)}, \quad (2.2)$$

where, for a given demand x of the activity, $E_1(x)$ is the total energy consumption in the initial situation, $E_2(x)$ is the total energy consumption in the new and more efficient situation (i.e., $E_2(x) < E_1(x)$), and X_1 and X_2 are respectively the initial and new demand of the activity. There is a rebound effect when $R > 0$, and even a *backfire* when $R > 1$, overshooting all the potential energy savings.

The rebound effect results from different economic and psychological *rebound mechanisms*, including cost savings, time savings, and economies of scale [49, 50]. They can occur at various levels, from the individual to the whole economy, and can be direct (specific to a particular product or sector) or indirect (arising between different products or sectors). It is important to note that the mechanisms driving the rebound effect are complex and extend beyond engineering. The rebound effect also applies to environmental indicators other than energy use, e.g., GHG emissions, water use, or chemical pollution. In order to meet the challenge of absolute environmental sustainability, technological innovations must account for the rebound effect and implement anti-rebound strategies [57].

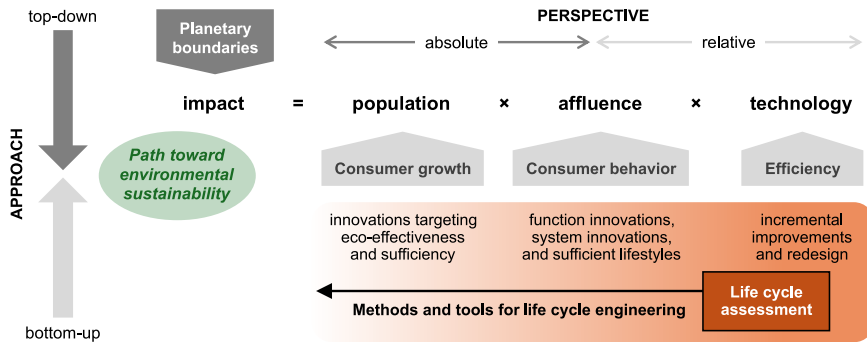


Fig. 2.7 Methods and tools for life cycle engineering in relation to the IPAT equation. The path toward environmental sustainability requires moving from a relative to an absolute perspective on environmental impacts and adopting both bottom-up and top-down assessment approaches (adapted from [63]).

2.2.2 Life cycle engineering

Engineering is a science-based practice of creating and designing technical solutions to perceived problems [57]. The proposed technical solutions are usually *products*, which can be goods or services. Traditionally, engineering focuses on *efficiency* aiming to maximize the functional performance or value creation of products while minimizing resource use or costs. LCE expands the perspective of engineering from the physical product to its entire life cycle, from cradle to grave. LCE then considers the *eco-efficiency* of products, which is defined as the ratio of the provided functionality or created value to the resource use or environmental impact over the full product life cycle. In the IPAT equation (2.1), the eco-efficiency is the inverse of the technology factor T . Usually, LCE methods and tools adopt a *relative perspective* on environmental impacts, focusing on incremental improvements in product eco-efficiency $1/T$, as illustrated in Figure 2.7.

Adopting an *absolute perspective* of environmental sustainability, Hauschild et al. [63] redefine LCE as “sustainability-oriented product development and manufacturing activities within the scope of one to several product life cycles, aiming to achieve sustainable manufacturing that allows fulfilling needs of both present and future generations without exceeding the boundaries of Earth’s life support systems”. Accordingly, they expand the traditional relative perspective of LCE to an absolute perspective by including innovations in function and systems that consider consumer behavior A , and, ultimately, eco-effectiveness and sufficiency to account for population growth P (see Figure 2.7). This suggests that LCE practitioners need to adopt a novel *top-down approach* alongside the traditional *bottom-up approach* to ensure that humanity remains within the SOS delineated by the planetary boundaries (see Section 2.1.3.1). To bridge the gap

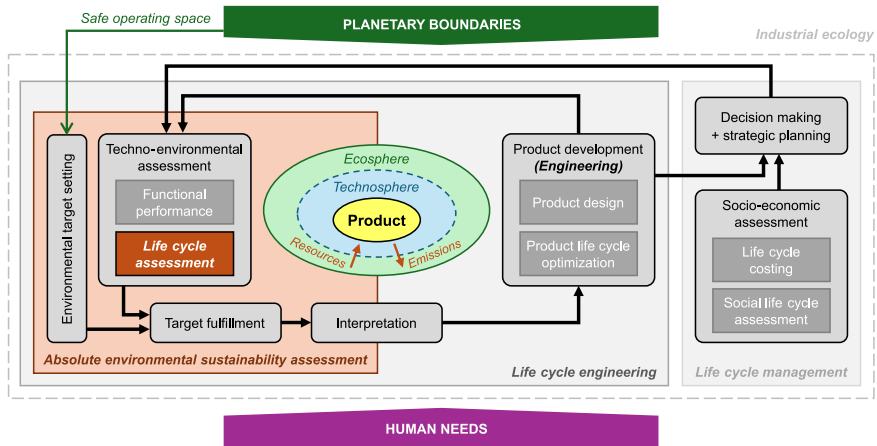


Fig. 2.8 Structured approach to operationalizing absolute environmental sustainability in engineering practices. This iterative approach centers around a product and consists of several successive steps. Anchored in industrial ecology, it is framed by planetary boundaries and human needs, and combines life cycle engineering and life cycle management. It integrates both the bottom-up life cycle assessment and the top-down absolute environmental sustainability assessment methodologies (adapted from [77]).

between bottom-up product engineering and top-down environmental target setting, Hauschild et al. [63, 77] propose a structured approach to operationalizing absolute environmental sustainability at the level of product development and management. Anchored in industrial ecology, this approach combines LCE with life cycle management (LCM), thereby promoting interdisciplinarity. Figure 2.8 presents a slightly adapted version of this approach.

Industrial ecology Industrial ecology is a discipline that studies the systemic relationships between society, the economy, and the natural environment [63, 77]. Grounded in this field, the structured approach to operationalizing absolute environmental sustainability is centered around the product, which is usually developed to provide a function that meets a human need. Thus, this approach is framed by planetary boundaries and human needs, similar to the Doughnut Economics framework (see Section 2.1.4). On one side, LCE carries out development and techno-environmental assessment of the product. On the other side, the organization offering the product performs techno-economic assessment and decision-making and strategic planning through LCM. Both LCE and LCM are interconnected and fall under the field of industrial ecology.

Technosphere and ecosphere The product life cycle takes place in the *technosphere*, which is embedded within the *ecosphere* [73]. The ecosphere is the ecological Earth system in which life exists, comprising the atmosphere, lithosphere,

cryosphere, hydrosphere, and biosphere (including humans). The technosphere (also known as the anthroposphere) is the Earth system that encompasses all elements and technologies made or modified by humans for human activities. The technosphere (and its human-made products) consumes resources from the ecosphere and releases emissions of pollutants and waste into it. Note that there is no clear-cut separation between the technosphere and the ecosphere.

Life cycle engineering LCE applies life-cycle thinking to the product development [63, 77]. The techno-environmental assessment step of LCE aims to assess the functional performance of the product before, during, and after its development. It also aims to assess the environmental impacts of the product throughout its entire life cycle using the LCA methodology. This method of assessing the eco-efficiency of products helps to reduce their direct environmental impacts, but cannot determine whether their environmental performance achieves absolute environmental sustainability. Therefore, the AESA methodology is used to allocate part of the SOS to the product. Through AESA, LCE starts by setting a top-down environmental target. Next, it uses the bottom-up LCA results to identify whether the environmental target is achieved. Finally, the interpretation step identifies the hotspots of environmental impacts in the product life cycle and quantifies the necessary improvements in order to fulfill the target. This interpretation step informs the product development step, which involves traditional engineering practices. This last step of LCE includes the product design and the product life cycle optimization. It investigates options for mitigating environmental impacts of the product at different levels. The LCE process can then continue iteratively.

Life cycle management LCM applies life-cycle thinking to the product management [63, 77]. This business approach organizes the normative, strategic, and operational management of the organization that offers the product (e.g., a company). In the structured approach of Figure 2.8, LCM aims at managing the entire product life cycle to promote sustainable consumption and production patterns. First, the LCM conducts a socio-economic assessment of the product using methods such as life cycle costing and social life cycle assessment. More importantly, LCM is responsible for the key steps of decision-making and strategic planning. These steps are informed by the socio-economic assessment and the mitigation options identified through LCE. This allows the organization to integrate environmental and human aspects into its decision-making and strategic planning to guide its operations toward absolute environmental sustainability.

2.2.3 Life cycle assessment

The LCA methodology is a science-based method of quantitatively assessing the potential environmental impacts of a product (i.e., a good or a service) [73]. It covers all stages of the product life cycle "from cradle to grave", including the raw materials acquisition, manufacturing, distribution, use, and end-of-life treatment

through disposal or recycling. In addition, LCA is a multi-indicator approach, assessing various environmental impact categories beyond climate change, e.g., water use, land use, ecotoxicity, resource depletion, etc. This comprehensive perspective allows LCA practitioners to identify eco-design trade-offs and prevent burden shifting between life cycle stages and across impact categories. LCA is used for various applications targeting eco-efficiency such as product development, product eco-design, support for decision-making, and environmental marketing. The LCA methodology is standardized by the ISO 14040:2006 [101] and ISO 14044:2006 [102]. This section, mainly based on Hauschild et al. [73], only covers the traditional process-based LCA approach, although other approaches exist. One noteworthy alternative is the environmentally extended input-output analysis, which is based on macro-economic systems analysis. For instance, consumption-based accounting of CO₂ emissions relies on this approach [4].

2.2.3.1 General principles and terminology

LCA is an environmental assessment of human needs fulfillment that first focuses on functions and then on the products needed to provide these functions [73]. Thus, a LCA study starts by precisely defining the studied *function* from the user perspective. A function is typically provided by one or more products that are part of a *product system* which contains all the *processes* necessary to fulfill that function. The function is described quantitatively by a *functional unit (FU)*, which serves as the basis for the rest of the LCA. This enables fair and relevant quantitative comparisons of alternative products that provide the studied function. In the product system, the amount of products needed to realize the FU are quantified by the *reference flows*, to which all input and output flows of the processes are scaled. In Figure 2.9, three reference flows are represented to fulfill the conceptual function throughout its cradle-to-grave life cycle: (i) a finished product ready for use, (ii) energy to operate the product during its use stage, and (iii) the used product ready for treatment at the end of its life.

In LCA, the life cycle inventory (LCI) model aims to link all processes occurring throughout the entire life cycle of the product to deliver the studied function [73]. In the LCI model, a *unit process* is the smallest element for which input and output flows are quantified. Unit processes can be considered as the building blocks of the LCI model and reference flows are the starting points for LCI modeling. In practice, a unit process may represent either a single process, e.g., rolling steel, or an entire facility containing many different processes, e.g., a slaughterhouse. The input physical flows of unit processes are materials, energy, and resources, while the output flows are products, wastes, and emissions.

In the LCI model, unit processes are linked such that the output flows belonging to the product or waste categories from one unit process can act as the input flows belonging to the materials and energy categories for other unit processes. In contrast, resources and emissions flows are not exchanged between unit processes

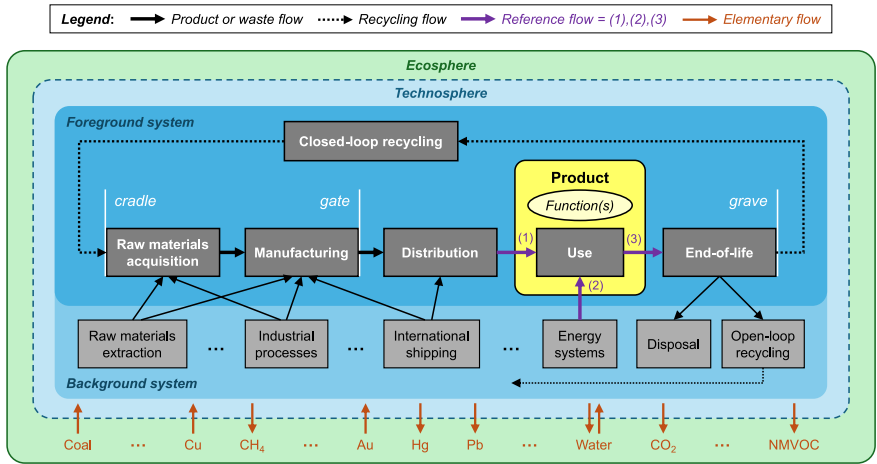


Fig. 2.9 Conceptual life cycle inventory model representing the unit processes of all life-cycle stages of a product delivering some function(s) by means of three reference flows. The "cradle", "gate", and "grave" of the life cycle are indicated at their typical locations. The technosphere is divided into foreground and background systems. Closed-loop (resp. open-loop) recycling occurs in the foreground (resp. background) system. Only elementary flows cross the boundary between technosphere and ecosphere (adapted from [73, 77]).

and are referred to as *elementary flows*. These flows consist of a single substance or energy entering the technosphere from the ecosphere without previous human transformation, or leaving the technosphere to be released into the ecosphere without subsequent human transformation. Therefore, elementary flows are the only flows that cross the boundary between the technosphere and the ecosphere, as shown in Figure 2.9.

The LCI model also distinguishes between the *foreground* and *background* systems [73]. The foreground system comprises all unit processes specific to the studied product. From a LCM perspective, the processes in the foreground system can often be modified by decision-making within the organization delivering the product (e.g., manufacturing processes). The foreground system is largely modeled using specific primary data, i.e., data known or measured by the organization. In contrast, the background system comprises all unit processes that are not specific to the product and are part of numerous product systems besides the one under study (e.g., energy systems). From a LCM perspective, processes in the background system usually cannot be structurally changed by the organization's decision-making. The background system is typically modeled using generic secondary data, i.e., large-scale average industry data. In general, LCI databases are used to source data for the background system, as well as for processes of the foreground system where specific primary data is unavailable.

2.2.3.2 Attributional and consequential modeling frameworks

Two main frameworks exist for LCI modeling: *attributional* and *consequential* [73]. Choosing between one framework over the other depends on the application targeted by the LCA study, and its perspective on environmental impacts and sustainability. The literature widely debates which framework to prefer in which case study, and there is still no consensus within the LCA community [103, 104].

Attributional life cycle assessment The goal of attributional life cycle assessment (ALCA) is to represent the product system under study in isolation from the rest of the technosphere [73]. The question addressed by ALCA is then "What portion of the total environmental impacts can be attributed to the studied product?" or "What environmental impacts is the studied product responsible for?" Yet, it is rather artificial to separate a product system from the rest of the technosphere because most products interact with others through multifunctional processes. A process is multifunctional when it provides more than one function or delivers more than one product output. In ALCA, multifunctionality poses a methodological challenge that can be addressed with three options, in order of priority: (i) subdivision of multifunctional processes, (ii) product system expansion, and (iii) allocation [105]. The third option requires applying normative criteria to allocate input, waste, and emission flows to the multiple output products. These criteria can be based on physical parameters (e.g., the mass or energy content of the output products) or on the utility of the output products (e.g., their economic value).

Consequential life cycle assessment The goal of consequential life cycle assessment (CLCA) is to identify the environmental impacts caused by a decision [73]. Unlike the attempt of ALCA to artificially separate a product from the rest of the technosphere, CLCA describes the changes to the technosphere caused by introducing the product, i.e., its consequences. Thus, CLCA addresses the question, "What are the global environmental consequences of delivering the studied product?" Consequential modeling relies on a solid understanding of the dynamics of the techno-economic system and requires a fundamentally different way of thinking than the traditional engineering perspective on supply chains adopted by ALCA. Another important difference with ALCA lies in the handling of multifunctional processes. In CLCA, multi-output processes are always handled by system expansion (when subdivision is not possible) because allocation does not align with the consequential perspective.

Figure 2.10(a) compares the ALCA and CLCA modeling frameworks from a temporal perspective. Considering the total environmental impact of the technosphere integrated over a time period (the "full pie"), ALCA attributes a portion of this impact to the life cycle of the studied product (a "piece of the pie") [104, 106]. In this case, the total environmental impact would be the sum of the environmental impacts of all separate final products. In addition, ALCA posits that the environ-

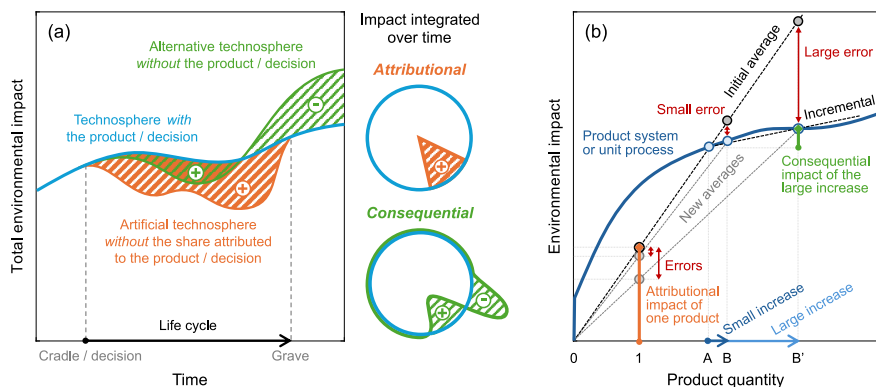


Fig. 2.10 Modeling frameworks of life cycle assessment: (a) the attributional (resp. consequential) impact of a product or decision is the difference between the total environmental impact of the technosphere with the studied product or decision, and the artificial technosphere without the share attributed to the product or decision (resp. the alternative technosphere without the product or decision), and (b) calculations and related errors of attributional and consequential impacts of a conceptual product system or unit process, using average and incremental models (adapted from [104, 106, 107]).

mental responsibility of using X products from a market is X times greater than the environmental responsibility of using one single product. Therefore, proportional models are used in ALCA to represent unit processes (see Figure 2.10(b)).

Conversely, CLCA analyzes how specific decisions, e.g., offering a product, affect the technosphere and its total environmental impact (the difference between the "full pie" and the "alternative pie" in Figure 2.10(a)) [104, 106]. In that case, the type of model used to represent consequential relationships is not limited to a linear model, as environmental mechanisms can be non-linear. Yet, the linear approximation of unit processes with marginal or incremental environmental responses is commonly used (see Figure 2.10(b)). Furthermore, the consequences resulting from a decision are not always limited in time, which usually requires setting an arbitrary time horizon in CLCA. In contrast, the time horizon of ALCA is typically bounded by the "cradle" and "grave" of the product life cycle. Though, these "boundaries" are also artificial, especially with regard to recycling.

For a non-linear product system or process, Figure 2.10(b) shows that using an average proportional extrapolation for a small increase in total product quantity (i.e., from A to B) does not result in a significant error in the attributed impact per product. However, for a larger increase (i.e., from A to B'), the average proportional extrapolation becomes quite erroneous, suggesting that using an incremental model is a better approach [107]. This does not mean that CLCA would necessarily be applied in that case (although it could be relevant). Rather, if ALCA is used, the impact of the entire product system or process must first be

calculated using an incremental model (i.e., from A to B' instead of using the initial average model for A). Then, a new proportional average model must be calculated per product unit for the new total product quantity (i.e., B').

For most applications, the choice between ALCA and CLCA is open [73, 104]. In general, ALCA is more feasible, comprehensible, inspiring, and robust than CLCA. Conversely, CLCA is, by definition, more accurate in guiding decision-making despite its potentially high uncertainty [104]. Some recommendations [73, 103, 104] indicate that ALCA is more suitable for environmental accounting and communication, as well as for supporting micro-level decision-making since it entails minimal transformation of the technosphere. In contrast, CLCA would be better suited for macro-level decision-making, which involves significant transformation of at least part of the technosphere. In some cases, it may also be wise to combine both frameworks as they offer complementary perspectives [104, 108]. Ultimately, it is up to the LCA practitioner to choose the appropriate framework to ensure that the LCA study is perceived as relevant by the target audience.

2.2.3.3 Methodological phases

The LCA methodology is a structured process comprising four phases: (i) goal and scope definition, (ii) inventory analysis, (iii) impact assessment, and (iv) interpretation. Instead of proceeding linearly, LCA involves many feedback loops between the phases, making it an iterative process [73].

Goal and scope definition The *goal* definition sets the context of the LCA study [73]. It includes the intended applications of the results, the decision context and reasons for carrying out the study, the target audience, etc. The goal definition then serves as the basis for the *scope* definition, which identifies the assessed product system and how the assessment is performed. The scope describes the studied function(s), FU, and reference flow(s), and defines the product system, determining its main life cycle activities and setting its geographical, temporal, and technological boundaries. Additionally, the scope definition establishes which life cycle impact assessment (LCIA) method (e.g., ReCiPe or Environmental Footprint (EF)) and LCI data sources (e.g., ecoinvent or primary data) are used in the study. It also sets the modeling framework, either ALCA or CLCA, and explains how multifunctionality is handled. The goal and scope definitions are important to consider when interpreting the results of a LCA study because they determine how the system is modeled and assessed. Therefore, they strongly influence the conclusions and recommendations drawn from the LCA results.

Inventory analysis The inventory analysis (also referred to as LCI analysis) collects information about all the unit processes identified as belonging to the product system [73]. The physical flows in the life cycle, i.e., the input flows of resources, materials, and energy, and the output flows of emissions, wastes, and products are

then scaled with respect to the corresponding reference flows. Often, the inventory analysis relies on generic data originating from LCI databases, which present input and output flows for numerous unit processes. The outcome of the inventory analysis is the LCI, which is a list of quantified elementary flows for the product system that provides the function described by the FU.

Impact assessment The impact assessment (also referred to as LCIA) translates the elementary flows of the LCI into environmental impacts using knowledge and models from environmental science [73]. The first step of LCIA is the *classification* that identifies all environmental issues to which each elementary flow can contribute (e.g., water depletion and non-renewable resource depletion). The next step is *characterization*, which translates the elementary flows of the LCI into the indicator scores of the environmental impact categories covered by the chosen standardized LCIA method. This process uses specific characterization factors, provided by the LCIA method, for each pair of elementary substances and environmental indicators. Hence, the characterization step essentially reduces a list of hundreds of quantified elementary flows to a manageable number of impact scores, typically around ten, with clear environmental meaning.

Two optional steps may then help to support the interpretation of LCIA results [73]. First, the *normalization* step aims to express the characterization results using a single metric for all impact categories. This serves for the audience to better understand the magnitude of the environmental indicator scores by relating them to a common familiar and external reference, typically the annual contributions to total environmental impacts of an average person. Then, the *weighting* step assigns a relative importance – a weight – to each impact category in order to make the normalized indicator scores comparable across categories. These weights are inherently subjective as they are based, e.g., on the opinions of experts, policymakers and/or the general public. Weighting enables the calculation of a single eco-score by summing all the weighted impact scores. This is often helpful for determining the "best overall" product option.

Interpretation The interpretation considers both results of the inventory analysis and the impact assessment to answer the question(s) posed as part of the goal definition [73]. The interpretation must take into account the goal and scope definitions and respect the restrictions imposed by the scoping choices on a meaningful interpretation of the results, e.g., due to system boundaries. Sensitivity analysis and uncertainty analysis are applied as part of the interpretation to guide the development of conclusions from the results, to appraise the robustness of the conclusions, and to identify areas for further work. The uncertainty of a result describes its statistical variation due to variability and error in the model parameters. The sensitivity of a model parameter describes the extent to which variation in that parameter affects the result of the model. Uncertainty analysis allows for the quantification of uncertainties in the LCIA result, as a consequence of the uncertainty of each parameter

in the LCI model, and sensitivity analysis allows for systematic identification of the parameters that have the highest influence on the LCIA results.

2.2.4 Absolute environmental sustainability assessment

While the LCA methodology can demonstrate that one product has a lower environmental impact than another, it cannot determine whether a product is sustainable in absolute terms. In other words, LCA can answer the question "Is it better?", but not "Is it good enough?" The relative perspective of LCA is therefore a major limitation because it does not necessarily lead to decision-making that achieves environmental sustainability in absolute terms, i.e., a society that meets human needs within Earth system boundaries [74, 75]. Thus, the AESA methodology aims to address this limitation by setting science-based absolute sustainability targets for individual human activities (e.g., products, companies or sectors).

Through AESA, each human activity is assigned a share of the safe operating space (SoSOS) or a share of other quantified absolute environmental thresholds. AESA is therefore a method for "down-scaling" the planetary boundaries, even though this concept was not initially designed for this purpose [41]. As such, AESA operationalizes the Planetary Boundaries framework, and allows decision-makers to apply "planetary boundaries thinking" to their strategic planning [76]. However, this methodology poses an ethical challenge regarding how to scale down the SOS into SoSOS in a fair and just manner [57]. Research on AESA is currently quite active and this methodology has not yet been standardized as it is still evolving.

2.2.4.1 General principles and terminology

The AESA is defined as the "assessment that evaluates the absolute environmental sustainability of an anthropogenic activity by comparing its estimated environmental impact to its assigned carrying capacity, taking a life cycle perspective and having complete coverage of impact categories" [74–76]. In this definition, an *anthropogenic activity* refers to a human activity involving multiple anthropogenic processes in order to deliver a function. In AESA, the scope of an anthropogenic activity ranges from a single consumer product to the global economy, including final products, companies and industry sectors. By comparison, LCAs generally target products, while the GHG Protocol targets companies.

The AESA community defines the *carrying capacity* as "the maximum persistent impact that the environment can sustain without suffering perceived unacceptable impairment of the functional integrity of its natural systems". The *assigned carrying capacity* is then the SoSOS allocated (or assigned) to the anthropogenic (or human) activity under study. However, this thesis prefers the less ambiguous term "safe operating space" to refer to "carrying capacity", as the latter also refers, in other disciplines, to the maximum population size of a biological species that can be sustained by an ecosystem (e.g., the human population on Earth). Comparing the environmental impacts of an anthropogenic activity to its assigned SoSOS allows

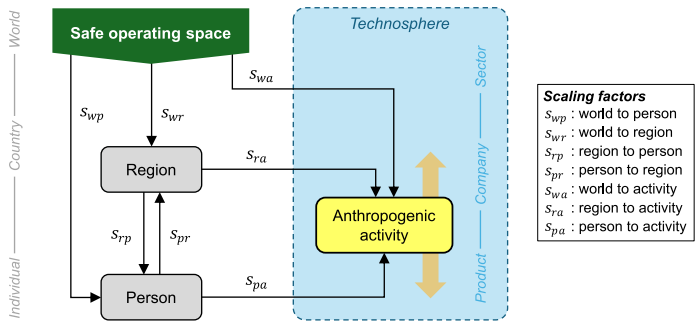


Fig. 2.11 Allocation process of the safe operating space to an anthropogenic activity. Its assigned share of the safe operating space is calculated via scaling factors over one or more steps through persons and/or regions, based on sharing principles (adapted from [75]).

for a *judgment* about the environmental sustainability of the activity with respect to the considered impact categories. An activity is judged to be environmentally sustainable if its environmental impacts are not greater than its assigned SoSOS.

Assigning a SoSOS to a single anthropogenic activity requires distributing the total SOS among all human activities based on one or more *sharing principles* [74–76, 109]. The AESA methodology allows to apply different sharing principles that are formalized in equations and linked to specific data. The choice of a sharing (or allocation) principle is normative, and different *ethical norms* underlie different principles. Figure 2.11 illustrates the allocation process from the SOS to the studied anthropogenic activity, which is part of the technosphere regardless its scale. The allocation process can be performed in one or more steps through an intermediary, such as a person or a region (e.g., a province, country, or continent).

The *scaling factor* from entity x to entity y , denoted by s_{xy} , is determined by the sharing principle between the two entities. It is common to refer to *down-scaling* for downward scaling (e.g., from the world to one person via s_{wp}) and *up-scaling* for upward scaling (e.g., from one person to a region via s_{pr}). It should be noted that even if it is mathematically possible to calculate an assigned SoSOS for individuals or regions, these entities are not anthropogenic activities. Rather, their assigned SoSOS represents their *right* to use this part of the SOS through their consumption and production patterns, but not their own direct environmental impacts. Indeed, environmental impacts considered in the context of sustainability only include those from the technosphere, not the biosphere (of which humans are a part).

2.2.4.2 Ethical norms and sharing principles

The process of allocating a SoSOS to a human activity is normative because it prescribes how the SOS should be divided [74, 76, 109]. This allocation can be based on ethical norms that define the conditions and criteria for the distribution. When

resources are scarce, ethical norms based on *distributive justice* theories prevail because they address the issue of distributing benefits and burdens in a "just" way among individuals. In fact, the safe operating space represents a scarce global resource that needs to be distributed among non-global entities, such as countries or persons. Contemporary political philosophy propose different distributive justice theories [74, 76, 109]. The four main ones are listed below.

- **Egalitarianism** All individuals should have equal rights.
- **Utilitarianism** The sum of welfare (e.g., the well-being of society) should always be maximized, regardless of potential inequality between individuals. However, defining and quantifying the welfare may be controversial.
- **Prioritarianism** The sum of prioritarian-weighted welfare should be maximized by giving priority, or higher rights, to the least advantaged individuals. Thus, a benefit has greater moral value when it benefits a person in a worse situation. As with utilitarianism, welfare must be defined and quantified, as well as the prioritarian-weighting perspective.
- **Sufficientarianism** Every individual should have "enough," suggesting a sufficiency level where those below the threshold have absolute priority over those above it. In that case, it is necessary to define and quantify what is "enough," which can be complicated.

Applying ethical norms from the distributive justice theories to share the SOS assumes that only human individuals have the right to use it, and that the SoSOS assigned to a region is based on its population size only. In that case, the allocation process must first scale down the SOS to the level of the individual (or a group of individuals in a region, e.g., a country) and then scale it – up or down – to a product, company or sector, according to relevant sharing principles [57, 109]. Another ethical norm for assigning SoSOS is **grandfathering**, which allocates the SOS among human activities based on their historical *acquired rights* or property, such as their contribution to environmental pressures or their occupied land area. Although some argue that an *inegalitarianism* theory supports the grandfathering norm by considering certain inequalities as just, it is generally considered unjust or unfair by the prevailing theories of distributive justice [74, 76, 109].

Examples of common sharing principles in AESA are given in Table 2.1, along with a brief description and the associated ethical norm [74, 76, 109]. In general, a combination of sharing principles must be applied when assigning a SoSOS, especially for small-scale activities. By contrast, a single stand-alone principle is usually employed for country-scale studies. For utilitarian sharing principles, the assigned SoSOS relates to the *utility* the activity provides to its users. Thus, the SoSOS assigned to companies or industry sectors depends on the number of users and their

Table 2.1 Examples of common sharing principles for allocating the safe operating space according to different ethical norms (adapted from [74, 75, 109])

Sharing principle	Ethical norm	Description
Equal per capita	Egalitarianism	Assigned SoSOS is the same for all individuals.
Economic value	Utilitarianism	Assigned SoSOS for an activity is proportional to its economic value.
Green incentive	Utilitarianism	Assigned SoSOS for a "green" activity is higher than its relative economic value.
Ability to pay	Prioritarianism	Assigned SoSOS for an activity is inversely related to its financial capacity.
Sufficiency lifestyle	Sufficientarianism	Assigned SoSOS for an activity is related to its share of use in a sufficiency lifestyle scenario.
Grandfathering	Grandfathering (or inequality)	Assigned SoSOS for an activity is proportional to its share of impacts in a past reference year.

assigned SoSOS, as well as the utility that these anthropogenic activities provide to their users. Determining the utility of activities is not straightforward and is mostly based on approximations from relevant available data. These approximations typically rely on economic indicators, such as GDP, gross value added (GVA), or final consumption expenditure (FCE).

The *grandfathering* principle is commonly applied to directly scale down the SOS to an activity based on its relative contribution to global environmental impacts in a past reference year. This direct and easy-to-use principle assumes a status quo in the distribution of environmental impacts. For instance, the SBTi uses this principle to allocate the global GHG emission reduction targets to companies, meaning they must all reduce their emissions at the same pace. The *equal per capita* principle is also commonly applied among individuals or regions and is often combined with a utilitarian principle for up-scaling to a specific anthropogenic activity. Among utilitarian principles, the *green incentive* favors "green" activities that have a high utility-to-environmental impact ratio. This principle aims to motivate companies to improve their eco-efficiency and favor those that promotes sustainable patterns. Similarly, but less common, the *sufficiency lifestyle* principle assigns to an activity a SoSOS proportional to its use in a sufficiency lifestyle scenario that targets fulfilling human needs by prioritizing sufficiency patterns. Lastly, an example of prioritarian principle is the *ability to pay* principle, which assigns a relatively higher SoSOS to activities or countries with lower-than-average financial capacity. Consequently, activities and countries with greater financial capacity are expected to lead the efforts toward sustainability.

Note that the AESA methodology does not prescribe preferring specific sharing principles over others. The choice of sharing principles for a given activity in a

specific AESA study depends on the context, objective and target audience of the study. Ultimately, an effective application of AESA at the global level requires consistently applying the sharing principles to avoid exceeding the absolute planetary boundaries. For instance, the allocation of the SOS among all countries should be based on a single sharing principle such that the sum of their SoSOS equals one. Yet, reaching a global consensus on which sharing principle to adopt would necessitate a vast debate among all countries. This would pose a significant political challenge, as demonstrated by the Conference of the Parties of the UN.

2.2.4.3 Methodological phases

The AESA methodology consists of three main phases: (i) estimating bottom-up the environmental impacts of the studied activity, (ii) allocating top-down the SOS to the activity, and (iii) interpreting the results by comparing the actual environmental impacts of the activity to its assigned SoSOS [75]. Figure 2.8 shows these AESA phases within the structured approach of LCE.

Environmental impact assessment The assessment of the environmental impacts of the studied activity adopts a life-cycle perspective and covers multiple categories of environmental impact [75]. This bottom-up assessment phase is mainly carried out by applying the LCA methodology.

Safe operating space allocation The allocation of the SOS to the studied anthropogenic activity translates top-down the global (or regional) planetary boundaries into the maximum allowable environmental impacts for that activity [75]. This allocation is inherently normative because it involves applying sharing principles related to ethical norms, particularly those determined by theories of distributive justice. It is often necessary to combine multiple sharing principles, particularly if the studied activity is a single product. The choice of sharing principles must be made transparent and justified, as it strongly affects the results and their interpretation. It is also recommended to apply multiple sharing principles as a sensitivity analysis and to clearly communicate the uncertainties.

Results interpretation The results are interpreted by comparing the estimated environmental impacts of the studied activity to its assigned SoSOS [75]. This yields an absolute sustainability ratio (ASR), which is the ratio between the actual impact of the product and the assigned SoSOS. If the environmental impacts are equal to or lower than the assigned SoSOS (i.e., $ASR \leq 1$), the activity can be considered environmentally sustainable. Otherwise (i.e., $ASR > 1$), impact reduction targets can be calculated and strategies for meeting these targets can be planned. The interpretation phase also involves evaluating the robustness of the results in light of uncertainties and normative choices.

2.3 Strategic planning for environmental sustainability

Strategic planning is a process used by organizations to define their long-term vision and objectives. Starting from an initial situation, strategic planning identifies opportunities and threats, elaborates plans, and allocates resources to effectively achieve the desired results. This process helps organizations adapt to change and make informed decisions about their future. Strategic planning is particularly relevant for addressing sustainability and environmental challenges [110, 111]. This section focuses on scenario development as a strategic planning approach. First, it describes the typology of scenarios in futures studies. Then, it details the backcasting method, which is the preferred method for developing long-term strategies that require an in-depth transformation of the initial system. Backcasting is thus particularly relevant for developing scenarios related to environmental sustainability.

2.3.1 Futures studies and scenarios

Futures studies is an interdisciplinary field that comprises a wide range of future-oriented approaches and techniques, particularly *scenario* development [112]. Future scenarios are often developed to address long-term challenges that are characterized by uncertainty and complexity. These challenges range from testing business plans to making public policies to anticipating future crises [110, 111]. Scenarios can provide insights into possible future trends and explore alternative future pathways. In general, scenarios do not have to be likely; they only need to be plausible and internally consistent [113].

2.3.1.1 Scenario typology

According to the classical typology proposed by Börjeson et al. [112], scenarios can be classified into three types: (i) *predictive*, (ii) *explorative*, and (iii) *normative*. These types respectively address the following questions: "What will happen?", "What can happen?", and "How can a specific target be reached?" The choice of a scenario type mainly depends on the time frame of the future-oriented study: predictive scenarios address short- to medium-term questions, whereas explorative and normative scenarios address medium- to long-term issues [113]. The choice also depends on the type of influencing factors analyzed: internal factors are controllable by the actor developing the scenario, while external factors are outside their scope of influence [112]. Table 2.2 summarizes the main characteristics of scenario types.

Predictive scenarios Predictive scenarios examine what is likely to happen in the short to medium term [111–113]. These scenarios are primarily used to plan for and adapt to expected situations within one given system structure, assuming that the laws governing the system will prevail during the analyzed time frame. As probability and likelihood are closely related to these scenarios, striving for accu-

Table 2.2 Main characteristics of scenario types in futures studies (adapted from [112])

Scenario	Time frame	System structures	Analyzed factors	Assessments
<i>Predictive:</i>		<i>"What will happen?"</i>		
Forecasts	Short to medium	One	External	Quantitative
What-if	Short to medium	One to several	External/internal	Quantitative
<i>Explorative:</i>		<i>"What can happen?"</i>		
External	Medium to long	Several	External	Quali./quanti.
Strategic	Medium to long	Several	Internal	Quali./quanti.
<i>Normative:</i>		<i>"How can a specific target be reached?"</i>		
Preserving	Long	One	External/internal	Quantitative
Transforming	(Very) long	One to several	External/internal	Quali./quanti.

racy and conducting an uncertainty analysis are important. Historical data often play an important role in developing scenarios. However, predictions can also be self-fulfilling, contributing to the preservation of past and present trends and making it more difficult to change undesirable ones. There are two types of predictive scenarios, which are distinguished by the conditions they impose on future events. *Forecast* scenarios are based on the most likely development, while *what-if* scenarios investigate the consequences of specified near-future events, such as internal decisions and/or external events.

Explorative scenarios Explorative scenarios describe what might happen in the medium to long term [111–113]. Similar to what-if scenarios, they cover a wide range of possible developments. However, they are developed with a longer time horizon to allow for structural and, consequently, more profound changes in the system. When assessing explorative scenarios, the level of accuracy and the importance of uncertainty analysis may be lower due to the longer time horizon and the greater degree of assumed change compared to the initial situation. There are two types of explorative scenarios, which are distinguished by the analyzed influencing factors. *External* scenarios focus only on factors beyond the control of the actor developing the scenario and do not include their policies or strategies. These scenarios provide a basis for assessing policies and formulating robust strategies. In contrast, *strategic* scenarios incorporate policy measures to describe the potential consequences of strategic decisions, focusing on internal factors.

Normative scenarios Normative scenario illuminates what ought to happen in the long term, typically 20–50 years, including changes in societal, economic and/or technological structures [111–113]. These scenarios are inherently normative because they target a desirable future and aim to identify how to achieve it. The result of a normative scenario study is typically several images of the future that fulfill the target, along with a discussion of the necessary changes in the

system to achieve them. Quantitative assessments of such long-term scenarios are usually challenging to perform. However, this is not a major issue because the purpose of these scenarios is to communicate the type and magnitude of the necessary system changes rather than to provide an exact evaluation of target fulfillment. There are two types of normative scenarios, which are distinguished by the changes in system structure. *Preserving* scenarios are used when it seems possible to reach the target within the prevailing structure of the system. These scenarios describe an optimum development within the given societal, economic and technological structures. In contrast, *transforming* scenarios are used when the target seems unreachable within the prevailing system structure, suggesting changes to societal, economic, and/or technological structures.

2.3.1.2 Scenario development techniques

Although the literature on the techniques for scenario development is diverse, Börjeson et al. [112] propose categorizing related techniques into three main categories.

- **Generating techniques** generate ideas and gather data, knowledge, and views about some aspect of the future (e.g., through workshops, panels, or interviews). The generating phase is very important in explorative and normative scenarios, for which it can be useful to involve stakeholders.
- **Integrating techniques** integrate the generated ideas into scenarios. A model structure facilitates the systematic collection of data and ensures that the different parts of the system are consistently described (e.g., based on mathematical modeling). These techniques focus on projecting development under explicit or implicit constraints. Modeling assumptions can be simple (e.g., extrapolating variables), or complex (e.g., assuming causal relationships between variables).
- **Consistency techniques** ensure consistency between or within scenarios.

In general, it is important to connect scenario development to the relevant policy process in order for such analysis to be useful in practice [114]. This requires moving beyond a purely analytical context to determine the behavioral and institutional responses to the scenarios and formulate the associated policy measures. A scenario study is likely to be fruitful if it involves the direct participation of the relevant stakeholders, e.g., the study commissioner or the relevant policy-makers. Furthermore, clear and transparent communication about future scenario studies is crucial, especially when conducting quantitative assessments [111]. Usually, stakeholders would expect to obtain as many and as precise details about the factors influencing the assessed scenarios. However, scenarios should sometimes avoid being too precise, considering that uncertainty in the scenario assessment can also serve as a basis for further strategic planning.

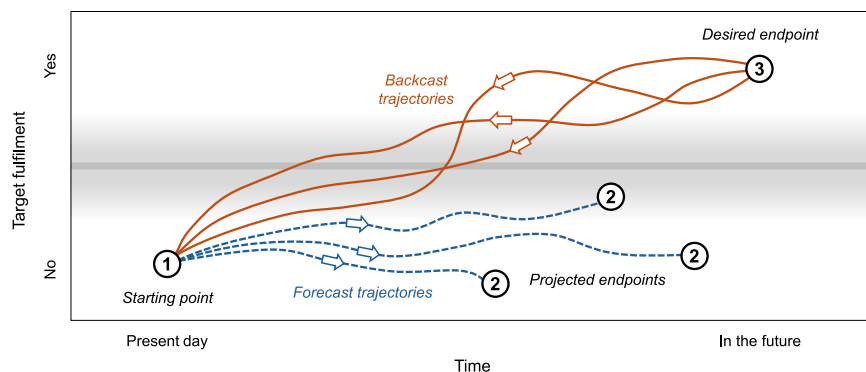


Fig. 2.12 Conceptual backcasting framework in which (1) a starting point is set in the present, (2) projected endpoints using forecasting do not fulfill the target, and (3) the desired endpoint that do fulfills the target is generated using suitable development techniques. Trajectories from (3) to (1) are then developed using backcasting (adapted from [116]).

2.3.2 Backcasting for environmental sustainability

Long-term forecasts are generally unreliable and tend to reflect the assumptions embedded in the model rather than predict the future. Furthermore, the most likely future is not necessarily the most *desirable* one. Therefore, in addition to making accurate predictions through forecasting, it is also useful to explore alternative possible futures, test their feasibility and potential impact, and determine how achievable they are [114, 115]. Unlike forecasting, which studies what the future is likely to be based on likelihood estimation, *backcasting* is intended to indicate the feasibility and implications of different futures based on their desirability. While the value of a predictive forecast is conventionally based on its accuracy, the value of backcasting lies in its ability to reveal potential alternative futures. As illustrated in Figure 2.12, the backcasting method involves working backward from a desired future endpoint, typically 20–50 years in the future, to determine the feasibility of that future and the policy measures required to reach it [114, 115]. Backcasting is thus inherently normative because it requires setting what constitutes a desirable future, and hence what does not. Thus, this approach primarily employs normative scenario, typically with a transforming perspective [115, 116].

Nevertheless, backcasting is often associated with forecasting. In backcasting, one or more forecasts are compared with a desired future vision. If the desired vision will not be reached according to the most reliable forecasts, the purpose of backcasting is to generate future scenarios that fulfill the targets expressed in the vision (see in Figure 2.12) [116]. However, backcasting is not optimization because optimization aims to identify efficient scenarios, while backcasting focuses on identifying scenarios that satisfy a long-term vision. Consequently, backcasting may result in scenarios that are expensive or inefficient in the short term and un-

likely to occur in the long term. Conversely, optimization may lead to short-term scenarios that hinder long-term target fulfillment, and are subject to the limited predictability of key influencing factors in the long term. Therefore, backcasting is preferable to optimization when the long-term target is considered more important than short-term efficiency, and vice versa [112].

The generic backcasting method proposed by Robinson [114] involves six steps.

- (1) **Determine objectives:** describe purpose of analysis, determine temporal, spatial and scope of analysis, and decide number and type of scenarios.
- (2) **Specify goals, constraints and targets:** set goals, constraints and targets for scenario analysis and for exogenous variables.
- (3) **Describe present system:** outline consumption and production processes.
- (4) **Specify exogenous variables:** develop description of exogenous variables and specify external inputs to scenario analysis.
- (5) **Undertake scenario analysis:** choose scenario generation approach, analyze future consumption and production processes, develop scenario(s), and iterate as required to achieve internal consistency.
- (6) **Undertake impact analysis:** consolidate scenario results, analyze social, economic and environmental impacts, compare obtained results with the goals, and iterate analysis as required to achieve goals and targets.

Finally, the method identifies an additional step that goes beyond the analytical scope of backcasting. This step determines the requirements for implementing a particular scenario through policy-making. As part of an iterative process, the policy-making then influences the objectives of subsequent backcasting studies.

The backcasting method can be applied to many different questions characterized by an orientation toward long-term problems. This method is generally appropriate when the problem to be studied is complex and affects many sectors and levels of society, when there is a need for major change, when dominant trends are part of the problem, and when the time horizon is long enough to allow time for debate and deliberation [115]. Thus, backcasting is a valuable method for supporting long-term strategic planning directed toward environmental sustainability [110, 114–116]. In this context, backcasting can be combined with the LCA methodology to conduct prospective LCA studies [111, 113, 117–119]. In these studies, the product system is placed within a background system that is consistent with a sustainable scenario determined through backcasting. Backcasting could also be integrated into the AESA methodology for the prospective allocation of the SOS, though prospective AESA has yet to be developed in the literature.

Summary

This chapter reviews frameworks and methods for environmental sustainability in engineering, laying the foundation for the research approach of the thesis. The concept of sustainability, which also includes a human dimension, has evolved from early debates about resource limitations to the SDGs. The weak and strong sustainability perspectives differ in their assumptions about the substitutability of natural and human-made capital. This thesis adopts the strong perspective, which considers certain critical environmental functions to be irreplaceable for human well-being. With a focus on environmental sustainability, the Planetary Boundaries framework defines a safe operating space for human societies across nine Earth system processes. Climate change is a core planetary boundary and constitutes the main focus of this thesis. The Doughnut Economics framework combines planetary boundaries and human needs to define a safe and just space for humanity between an ecological ceiling and a social foundation. Environmental sustainability can be operationalized in engineering practices through LCE, which centers on products and integrates both the bottom-up LCA and the top-down AESA methodologies. LCA is the standard methodology for assessing the environmental impacts of a product's life cycle across multiple categories. AESA then compares these relative results against normative environmental budgets. These budgets are assigned to the product by scaling absolute environmental targets based on sharing principles. Strategic planning can leverage futures studies and backcasting to develop prospective scenarios that align with environmental sustainability goals.

3

State-of-the-art models and assessments of radio access networks

In this thesis, the RAN constitutes the product – or anthropogenic activity – under study. It provides wireless communication services to mobile UEs, which can be digital interfaces for human subscribers or connected objects. In practice, RANs are operated by MNOs and comprise numerous BSs deployed across a territory to provide coverage for most UEs. Before developing an integrated parametric model for RANs in Part I, and applying this model in Part II, this chapter reviews the state of the art on RAN models and assessments. Thus, this chapter establishes the scientific foundation for the contributions of this thesis.

This chapter begins with a review of the literature on environmental impact assessments of mobile networks in Section 3.1. This section focuses exclusively on direct (first-order) impacts, as indirect (higher-order) impacts fall outside the scope of this thesis. Then, Section 3.2 reviews the literature on models for QoS, energy consumption, and life-cycle environmental impacts of RANs, including integrated network models and simulators, as well as specific BS models. These two sections also explicitly identify research gaps in the existing literature. Finally, Section 3.3 summarizes the main research gaps and relates them to the three research questions addressed in this thesis. This chapter builds upon literature reviews performed in [JP1], [CP2], and [JP3], as well as insights from [JP2].

3.1 Environmental impact assessments of mobile networks

This section reviews the literature on the direct environmental impacts of mobile networks operating under realistic conditions. This review identifies two main categories of relevant studies: (i) studies assessing relative environmental performance indicators, and (ii) studies assessing the absolute future impacts of mobile networks through prospective country-level scenarios. Most existing studies focus on the operational energy consumption and carbon footprint of the networks. Accordingly, this section is limited to these two indicators. Yet, before reviewing the studies, this section introduces four key methodological aspects of mobile network assessments. Then, the section discusses energy intensity assessments and, finally, reviews prospective country-level assessments.

3.1.1 Key methodological aspects

Four key methodological aspects emerge from studies assessing the direct environmental impacts of mobile networks: (i) the scope definition, (ii) the modeling approach, (iii) the time perspective, and (iv) the modeling framework.

First, the scope definition generally specifies the time period, geographic region, life-cycle stages, and system boundaries of the study. In particular, the **technological boundaries** of mobile networks may be defined in relation to the ICT sector. Figure 3.1 illustrates one possible representation of the ICT sector (proposed by Malmudin et al. [26]), including the three traditional subsectors: (i) UEs, (ii) networks, and (iii) data centers, as well as operator activities. Since the ICT sector is continuously evolving, it may also encompass new connected devices (e.g., IoT sensors and connected vehicles), new types of communication networks (e.g., satellite networks), etc. However, the specific definition of the ICT sector may vary across studies [6, 7] and may rely on different criteria, as discussed in [JP2]. For instance, Figure 3.1 identifies an associated entertainment and media (E&M) sector, some of whose elements may also be included in the ICT sector depending on the adopted perspective. Therefore, clearly defining the technological boundaries of the study is essential for ensuring the comparability and interpretability of results. When assessing mobile networks, this mainly concerns whether certain BS components, the core network, and operator activities are included in the scope.

Second, mobile networks at a given scale (e.g., local, national, or global) can be assessed using either a top-down or bottom-up modeling approach [53, 54, 120].

- **Top-down** approaches are based on high-level statistics that are downscaled to the target network scale. For example, the electricity consumption of mobile networks in a given country is calculated by downscaling the global electricity consumption of mobile networks from its share of data traffic.
- **Bottom-up** approaches are based on low-level models and empirical data that are aggregated at the target network scale. For example, the electricity

consumption of mobile networks in a given country is calculated by adding up the consumption of its individual components.

Thus, both modeling approaches can be used to assess mobile networks on a given scale but differ in the level of granularity and the nature of input data required. Moreover, the two approaches have different intended applications [120]. Since top-down assessments treat the network as a black box, they do not require detailed knowledge of the network architecture. However, they cannot be used to evaluate specific changes within the network but only high-level trends. Bottom-up assessments, in contrast, facilitate evaluating alternative design choices at different network levels. However, this modeling approach is naturally constrained by the increasing model complexity that comes with added levels of detail. To deal with these issues, some studies propose hybrid modeling approaches that combine the top-down and bottom-up approaches.

Third, a mobile network assessment can have either a retrospective or a prospective time perspective [117, 118].

- A **retrospective** study looks back to assess mobile networks as they actually were at a point in the past relative to the time of conducting the study.
- A **prospective** study looks forward to assess mobile networks as they could potentially be at a point in time in the future relative to the time of conducting the study.

These two assessment perspectives differ primarily in terms of the type of data that can be used. Retrospective studies can be based on observations of actual past network deployments, while prospective studies must formulate assumptions about possible future network developments that cannot be observed in advance. Therefore, the two perspectives also differ in their methodology. Prospective studies must establish one or more future scenarios (e.g., using methods of futures studies, as introduced in Section 2.3), while the scenario that has unfolded in the past is known in advance for retrospective studies. Moreover, prospective studies usually assess entire scenario trajectories between the initial state and future endpoints, identifying cause-and-effect relationships, whereas retrospective studies usually target single point estimates.

Lastly, the modeling framework can be **attributional** or **consequential**, as introduced in Section 2.2.3 for the LCA methodology. The choice between these two modeling frameworks depends on the specific goal of the study [73, 103, 104]. The attributional framework usually focuses on environmental accounting and communication about mobile networks, and is better suited to supporting micro-level decision-making. Typically, it is also more feasible, comprehensible, and robust than the consequential modeling framework. In contrast, the consequential framework is, by definition, more accurate in guiding decision-making, especially at the macro level, despite its potentially higher uncertainty. Retrospective assessments

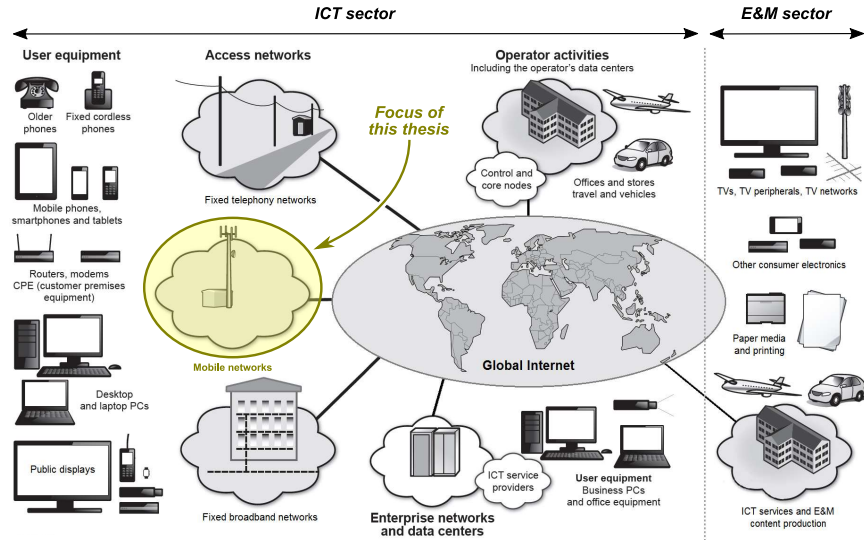


Fig. 3.1 Illustrative representation of the information and communication technology (ICT) sector, including the three traditional subsectors (i.e., user equipment, networks, and data centers), operator activities, and the entertainment and media (E&M) sector. Today, new types of devices, networks, etc., could also be included in these sectors. Within the ICT sector, this thesis focuses on mobile networks (adapted from [26]).

of mobile networks generally use the attributional modeling framework for the target past year, while prospective assessments may use either attributional or consequential modeling frameworks for assessing future scenarios. When using the consequential framework, one major challenge is defining a relevant baseline (or reference) scenario, which must be clearly described and discussed [72, 121]. The consequential framework is also preferred for assessing the indirect effects of mobile networks, which goes beyond the scope of this section.

Alongside these four methodological aspects, it is important to note that uncertainty and sensitivity analyses remain largely underdeveloped in the literature. In particular, most studies report only "typical" point estimates despite the strong dependence on modeling assumptions. Therefore, more systematic uncertainty quantification and sensitivity analysis would significantly improve the transparency and interpretability of mobile network assessments. Accordingly, this thesis pays particular attention to uncertainty quantification and analysis.

3.1.2 Energy intensity assessments

The environmental performance of mobile networks is traditionally measured using energy intensity metrics. A common approach to calculate such a relative in-

indicator is to divide the network energy consumption by the transferred data volume, which is generally expressed in kilowatt-hours per gigabyte (kWh/GB) or Joules per bit (J/bit) [120]. Other energy intensity metrics are also used, such as annual energy consumption per subscription (kWh/sub/year), per area covered (kWh/km²/year), etc. By definition, all these metrics adopt an attributional modeling framework, in which an average amount of energy is allocated per unit of service provided. Shifting from a relative to an absolute perspective, the total energy consumption of mobile networks can then be estimated by combining the energy intensity metrics with the total amount of service provided (e.g., following the IPAT equation introduced in Section 2.2.1).

Based on a literature review conducted by Pirson [122], Figure 3.2 shows the evolution of energy intensity assessments for mobile networks between 2005 and 2030. The studies included in this figure are Golard et al. [JP1] (conducted prior to this thesis), Malmudin et al. [25–27, 30, 31, 123], Andrae et al. [124, 125], Pihkola et al. [126], Schien et al. [127], and Teehan [128]. Figure 3.2(a) focuses on the widely used energy intensity metric expressed in kWh/GB. It reveals a pronounced downward trend over time, from >10 kWh/GB before 2010 to around 0.1 kWh/GB after 2020, which corresponds to an improvement of about one order of magnitude every five years. Although technological advances in mobile networks have contributed to this improvement, another main driver is the dramatic growth in mobile data traffic volume. To counteract the high sensitivity of the kWh/GB metric to traffic growth, Malmudin et al. [25–27, 30, 31, 123] instead suggest studying the energy intensity of communication networks in kWh/sub/year. Accordingly, Figure 3.2(b) shows that this alternative metric is much more stable over time, remaining around 15–20 kWh/sub/year, with only a slight downward trend.

Despite the overall consistency of the results presented in Figure 3.2, some variability remains across studies. Part of this variability can be attributed to uncertainty in the assessments, while methodological differences also play a significant role. First, the technological boundaries of mobile networks vary between studies. Although all studies include RANs, some also account for operator-specific activities and parts of the core network or backhaul. Nevertheless, the effect of these scope discrepancies is expected to be limited given that RANs account for at least 4/5 of the total electricity consumption of mobile networks [27, 30, 31]. Furthermore, the targeted region varies across studies. While most of them adopt a global perspective, Teehan [128] focuses on the United States, Pihkola et al. [126] target Finland, and Golard et al. [JP1] study RANs in Belgium. Differences in modeling approaches also contribute to variability, as studies may rely on bottom-up, top-down, or hybrid approaches. Finally, the time perspective influences uncertainty because retrospective assessments can draw on historical data, whereas prospective assessments necessarily rely on assumptions about future developments.

Nevertheless, energy intensity metrics suffer from two major limitations. First, these relative metrics exhibit poor proportionality with the level of service pro-

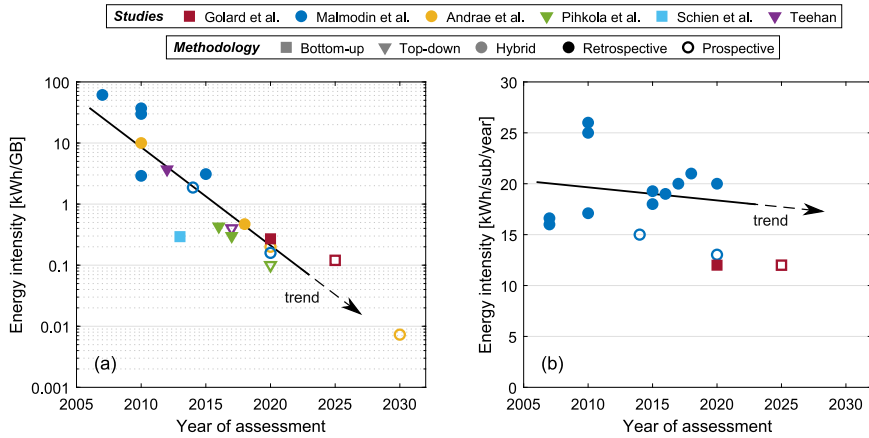


Fig. 3.2 State-of-the-art assessments of energy intensity metrics for mobile networks (a) per gigabyte of data traffic, and (b) per subscription per year. From 2005 to 2025, the per-GB metric improved about $\times 10$ every five years, while the per-sub-year metric remained fairly stable. Examined studies are Golard et al. [JP1], Malmodin et al. [25–27, 30, 31, 123], Andrae et al. [124, 125], Pihkola et al. [126], Schien et al. [127], and Teehan [128]. Methodological differences partly explain the variability in assessment results.

vided (e.g., data traffic volume), both in the short and long term [129, 130]. In the short term, the energy intensity fluctuates with the actual amount of service provided due to the substantial share of static (load-independent) power consumption in network components compared to their dynamic (load-dependent) power. In the long term, projecting the energy intensity metrics requires assumptions about their relationship with the provided service, which is difficult to characterize. Second, relative intensity metrics inherently hide absolute impacts [129], as providing more service can improve efficiency through scaling effects while simultaneously increasing total energy consumption. In contrast, sufficiency-oriented strategies may reduce absolute impacts even if they lead to lower energy efficiency. For example, the absolute electricity consumption of mobile networks worldwide increased from 85 to 161 TWh between 2010 and 2020 [26, 27], while the energy efficiency improved by around $\times 50$ over the same period (see Figure 3.2(a)).

Overall, this review of energy intensity metrics raises a key question for mobile networks: can the trends observed in Figure 3.2 continue in the future? More specifically, would increases in data traffic and subscription numbers alone lead to continuous improvement in energy intensity metrics, or are targeted technological interventions required? In the latter case, which specific measures should be prioritized to achieve the greatest efficiency gains? These questions motivate further investigation into designing energy-efficient BSs under realistic operating conditions. However, energy intensity metrics alone are insufficient for informed

decision-making because they only provide a relative perspective on the network environmental performance. This limitation underscores the necessity of complementing relative performance indicators with absolute network assessments.

3.1.3 Prospective country-level assessments

Prospective assessments of mobile networks primarily aim to inform long-term decision-making and strategic planning at the policy and industry levels (e.g., regarding sustainability goals). Typically, they formulate recommendations for stakeholders, including designers, businesses, policymakers, and consumers [110]. The prospective aspect of these studies involves establishing a reference year and a future time horizon over which the scenarios are developed. These scenarios include at least one baseline (e.g., "business as usual") and possibly alternative scenarios based on other narratives [35]. Since key decisions regarding mobile networks are usually made at the country level (e.g., by MNOs and regulators), this scale is particularly relevant for these studies. At this scale, a bottom-up modeling approach is generally required to represent the heterogeneous deployments across the country and to assess scenarios that diverge from basic forecasts. For practical reasons, most studies adopt an attributional modeling framework, although a consequential framework may be used when interpreting differences between the baseline and alternative scenarios [72, 121].

In the literature, four recent studies develop and assess prospective scenarios for mobile networks at the country level: Golard et al. [JP1] in Belgium, Stobbe et al. [37] in Germany, The Shift Project [38] in France, and Bieser et al. [36] in Switzerland. Most of these studies use 2020 as the reference year (except in Stobbe et al. [37], which uses 2019) and extend to 2030 (except in Golard et al. [JP1], which only extends to 2025). Each study investigates at least one baseline scenario using a predictive approach, and up to seven alternative scenarios using both predictive and explorative approaches. These scenarios are mainly constructed along two dimensions: the supply (e.g., RAN deployment strategies by MNOs), and the demand (e.g., data traffic and usage patterns by network users). On the supply side, alternative strategies in Golard et al. [JP1] include doing nothing or implementing sleep modes, sharing networks by MNOs or deploying small-cell BSs in Stobbe et al. [37], and eco-designing RANs in The Shift Project [38]. On the demand side, Golard et al. [JP1] also investigate a rebound in data traffic, while The Shift Project [38] examines sufficiency-oriented usage patterns. Note that Bieser et al. [36] consider only a single baseline scenario.

Figure 3.3 summarizes the scenario trajectories across the four studies. Figure 3.3(a) depicts the annual electricity consumption and Figure 3.3(b) shows the corresponding annual GHG emissions, including the production stage. To enable comparison across countries, all trajectories are indexed to 1 in the reference year 2020. Note that the plotted results account for RANs only, hence excluding core network assessments by Stobbe et al. [37] and Bieser et al. [36]. In Figure 3.3(a), base-

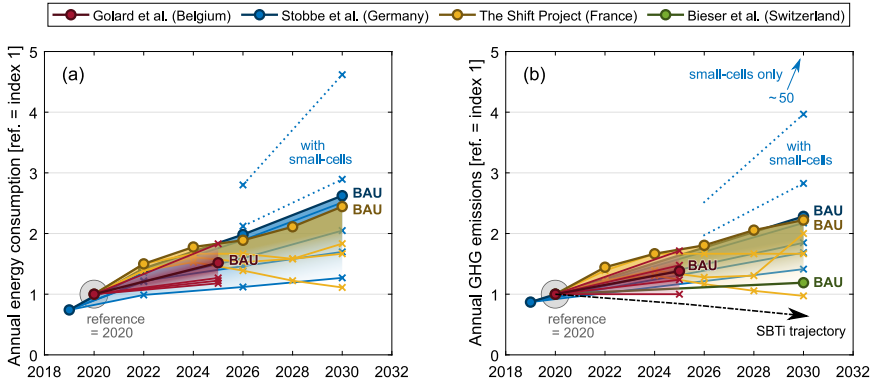


Fig. 3.3 Trajectories of prospective scenarios from 2020 to 2030 for radio access networks at the country level in terms of (a) the annual energy consumption, and (b) the annual greenhouse gas (GHG) emissions. Examined studies are Golard et al. [JP1] in Belgium, Stobbe et al. [37] in Germany, The Shift Project [38] in France, and Bieser et al. [36] in Switzerland. All baseline ("BAU") and alternative scenarios either remain stable or increase over time, but none of them aligns with the SBTi trajectory.

line scenarios indicate that the RAN energy consumption would increase $\times 2$ - 2.6 between 2020 and 2030, whereas a combination of eco-efficient deployment strategies and a slowdown in usage growth would nearly stabilize energy consumption over this period. Conversely, a rebound in usage or the massive deployment of small-cell BSs (outdoor and indoor using mmWave) would lead to a rise in energy consumption of up to $\times 4.6$ over 2020-2030. Similarly, the baseline scenarios in Figure 3.3(b) indicate that GHG emissions from RANs could increase $\times 1.2$ - 2.2 between 2020 and 2030, and would remain stable in the best case scenarios. As for energy consumption, the massive deployment of small-cell BSs in Germany would increase $\times 4$ the GHG emissions of RANs. Stobbe et al. [37] further estimate that decommissioning all large-cell BSs in favor of small-cells only throughout the whole country could increase $\times 50$ the GHG emissions over 2020-2030.

Since the use stage significantly contributes to the carbon footprint of RANs, decarbonizing the electricity grid is a key lever for reducing the GHG emissions of mobile networks. For instance, Golard et al. [JP1] assume a reduction in the carbon intensity of the grid from 223 to 192 gCO₂eq/kWh in Belgium over 2020-2025, and Stobbe et al. [37] assume a reduction from 400 to 280 gCO₂eq/kWh in Germany over 2019-2030. Alongside this external lever, Stobbe et al. [37] and The Shift Project [38] provide specific recommendations for decarbonizing mobile networks. Both studies first recommend modernizing networks through technological advances and eco-design. Notably, new architectures and semiconductor technologies could improve the efficiency of power amplifiers (PAs) in the radio modules. The studies also recommend optimizing the capacity planning to avoid oversizing

BSs. Additionally, they suggest implementing sleep modes and dynamic activation of radio resources to maximize their utilization. Stobbe et al. [37] also suggest coordinating RAN deployment strategies at the country level to enable network sharing by MNOs. Furthermore, The Shift Project [38] points out that decarbonizing mobile networks requires not only technical developments but also societal and political choices. Specifically, this study argues for sufficiency-oriented measures, including QoS trade-offs and targeted usage prioritization. Finally, both studies stress that improving the transparency and reliability of environmental impact assessments of network components, particularly at the production stage, is necessary to raise stakeholder awareness and better inform decision-making.

In summary, this review of prospective studies on mobile networks shows that specific alternative scenarios outperform baseline scenarios in terms of absolute energy consumption and carbon footprint. However, Figure 3.3(b) indicates that none of the reviewed scenarios aligns with the SBTi trajectory set by the ITU. Thus, a second key motivation for conducting this thesis is to explore new prospective scenarios for RANs that could meet this target at the country level. Building on [JP1], this thesis examines Belgium as a specific case study. The reviewed studies also emphasize the importance of implementing efficiency- and sufficiency-oriented measures on both the supply and demand sides. Nevertheless, further quantifying the recommendations of these studies would help prioritize technological improvements and identify the most effective levers for decarbonizing mobile Internet access. This constitutes another motivation for this thesis.

3.2 Radio access network models

This section reviews the literature on RAN models designed to assess QoS and life-cycle environmental impacts. It first examines integrated network models and simulators that account for multiple BSs to evaluate RAN performance at the network level. Since these tools are generally constructed bottom-up from the BS level, the section then reviews existing BSs models that serve as building blocks for RAN models. Specifically, the review addresses three key aspects of BS performance that are usually modeled separately: (i) communication performance, (ii) power consumption, and (iii) life-cycle environmental impacts.

3.2.1 Integrated network models and simulators

Integrated network models and simulators are designed to evaluate RAN performance, focusing primarily on data throughput and operational energy consumption. Targeting network-level evaluations, these tools generally adopt a bottom-up modeling approach to account for multiple BSs. Since they also aim to support network planning and BS design, these tools typically rely on physics-based models of network components and wireless communications. In the literature, two main cat-

egories of integrated network evaluation tools are identified: (i) generic evaluation frameworks, and (ii) location-specific simulators.

Generic evaluation frameworks typically target RAN evaluation at the country level, providing support for large-scale deployment strategies rather than optimizing specific BS deployments. One widely used framework is the energy efficiency evaluation framework (E^3F) proposed by Auer et al. [131]. As illustrated in Figure 3.4(a), this framework first performs system-level evaluations of power consumption and QoS metrics at small scales (i.e., for a set of representative deployment areas) and over the short term (i.e., for different traffic levels). These short-term area-specific metrics are then aggregated to derive global performance metrics at a large scale (i.e., for one country) and over the long term (i.e., for an average traffic profile). The aggregation relies on the statistical distributions of deployment areas and the daily data traffic profile for the examined country (see Figures 3.4(b) and 3.4(c) for a typical European country). The E^3F is subsequently extended for 5G-NR networks by Chen et al. [132], Olsson et al. [133] and Peesapati et al. [134]. Similar frameworks are also proposed for heterogeneous 4G-LTE networks by Lorincz and Matijevic [135] and Virdis et al. [136], combining macrocell and microcell BSs. Björnson et al. [137] propose an additional framework for the analytical evaluation of massive-MIMO networks. Overall, these frameworks enable the macro-level optimization of communication and energy performances of RANs, as in Peesapati et al. [138, 139] using reinforcement learning.

In contrast, *location-specific simulators* evaluate RANs at a finer spatial resolution within specific geographic environments. These simulators usually aim to optimize the placement of specific BSs within an area, primarily with respect to QoS, and but also with regard to energy consumption. Among these simulators, some are freely available as open-source software, typically for academic – sometimes non-commercial – use. For instance, the VIENNA simulators [140–142], developed using MATLAB, enable link- and system-level simulations of 4G-LTE and 5G-NR networks. Comparable tools based on the NS-3 network simulator provide full-stack simulations of 4G-LTE and 5G-NR networks [143–147]. Other simulators are proprietary and may require paid licenses. For instance, MATLAB provides dedicated toolboxes [148, 149] for simulating and prototyping 4G-LTE and 5G-NR networks, from the physical layer to network architectures. Another example is the SIMONE simulator [150] that focuses on 2G-GSM to 5G-NR RAN planning optimization by integrating ray-tracing techniques. Lastly, the network deployment tool developed by the WAVES research group [151–155] aims to optimize the deployment of 4G-LTE and 5G-NR BSs – including mmWave bands – by jointly minimizing power consumption and electromagnetic field exposure.

This literature review reveals that generic frameworks, such as the widely used E^3F [131–134], enable the joint evaluation of communication and energy performances of RANs at the country level. In contrast, location-specific simulators target more detailed evaluations and optimizations of RAN deployments at local scales.

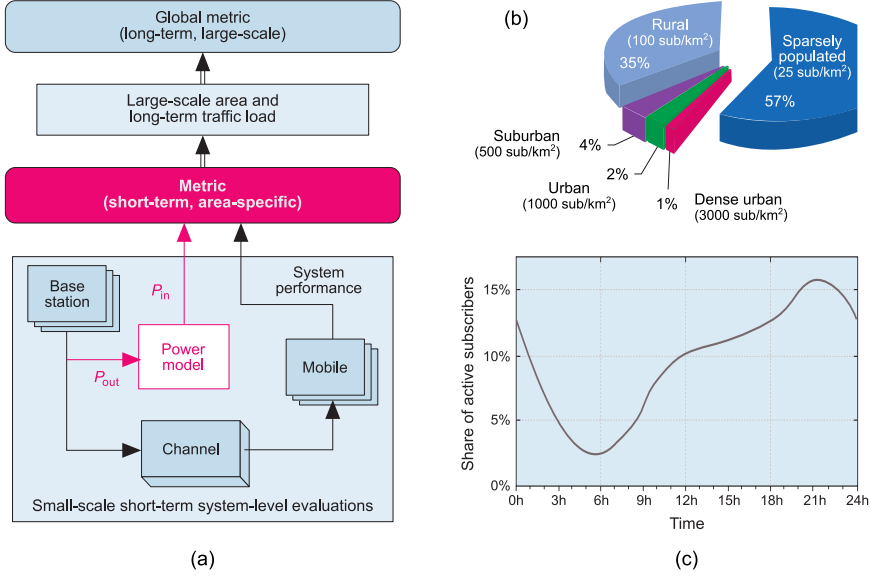


Fig. 3.4 Generic energy efficiency evaluation framework (E^3F) for assessing large-scale long-term performance of radio access networks by aggregating small-scale short-term system-level evaluations: (a) framework structure, (b) typical distribution of deployment areas in Europe, and (c) typical daily data traffic profile in Europe (adapted from [131]).

However, existing simulators rarely capture the realistic power consumption of BS components. Moreover, the few energy-oriented simulators [151–155] are not open source, which prevents their integration with generic frameworks for detailed RAN evaluations to the country level. More fundamentally, none of the reviewed frameworks or simulators explicitly assesses the environmental impacts of BSs throughout their entire life cycle. This reveals a clear need for integrated network evaluation tools that combine the physical realism of location-specific simulators with the large-scale long-term perspective of generic evaluation frameworks. These tools should specifically enable the assessment of life-cycle environmental impacts of BSs and be made available open source to support further research. Addressing this gap motivates the development of an integrated RAN model in this thesis, enabling the simultaneous assessment of the communication and environmental performances of mobile networks.

3.2.2 Base station communication performance models

The study of wireless communications and cellular networks primarily falls within the research fields of information theory and signal processing. In general, studying these topics requires accounting for the characteristics of connected UEs (e.g.,

the number of receive antennas), radio channel conditions (e.g., urban or rural environment), and the effects of interference (typically originating from neighboring BSs), in addition to BS specifications [134, 137, 140, 153]. Evaluations of mobile network communication performance usually focus on the downlink (DL) (i.e., from the BS to UEs) because it is widely considered the bottleneck, although the uplink (UL) (i.e., from UEs to the BS) is also extensively studied. In the DL, typical QoS metrics include overall BS data throughput, average data throughput per UE, cell-edge throughput, cell coverage or outage probability, and packet transmission latency. The rest of this section first reviews key references on wireless communications and mobile network protocols. Then, it presents the link abstraction strategy for simulating wireless networks, illustrated by a 4G-LTE RAN simulator.

A key reference on the fundamentals of wireless communications is Tse and Viswanath [156], which covers physical channel modeling, wireless channel diversity, channel capacity estimation, and multi-user communications. It also introduces the basics of cellular systems. Another interesting reference on MIMO technology for wireless communications is Tsoulos [157]. More recently, Björnson et al. [158] further elaborate on massive MIMO for cellular networks, addressing spectral efficiency, energy efficiency, and hardware efficiency, as well as practical deployment considerations. While these references establish a strong theoretical foundation, they generally remain agnostic to the practical mechanisms and constraints of communication protocols implemented in real mobile networks. Thus, Khan [12] provides a practical introduction to 4G-LTE technologies, notably describing network architectures, radio channel structures, DL and UL signaling, scheduling and link adaptation strategies, and inter-cell interference coordination (ICIC). From a more implementation-oriented perspective, Dahlman et al. [13] offer detailed descriptions of the latest version of 4G-LTE, followed by Dahlman et al. [14] for the 5G-NR protocol. While these references offer useful protocol overviews, the original standards published by the 3rd Generation Partnership Project (3GPP) may also be consulted to clarify subtle protocol details, such as [159] and [160] for the modulation of 4G-LTE and 5G-NR signals.

As described by Cavalcanti et al. [161], wireless network simulations are commonly divided into two levels: (i) link-level simulations, and (ii) system-level simulations (see Figure 3.5). *Link-level simulations* assess the performance of individual radio links for specific connections established between a BS and a UE. As shown in Figure 3.5(a), these simulations investigate physical layer operations such as source and channel coding and decoding, signal modulation and demodulation, and radio wave propagation. These simulations are, in turn, representative of links in similar conditions throughout the network. However, the large number of BSs and UEs in mobile networks makes it impractical to evaluate entire networks solely through link-level simulations. Instead, *system-level simulations* assess network-related performance across multiple radio links for simultaneous connections. As shown in Figure 3.5(b), these simulations investigate high-level network issues such as traf-

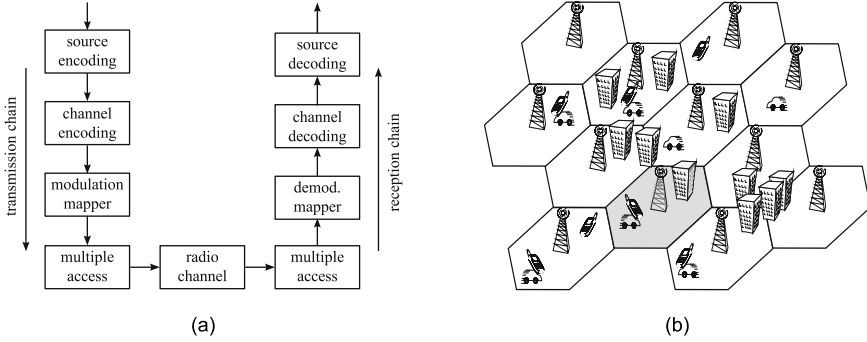


Fig. 3.5 Scope of (a) link-level simulations and (b) system-level simulations in wireless network simulators. Link-level simulations focus on the physical layer operations for specific radio links, whereas system-level simulations consider multiple radio links across simultaneous connections throughout the network. A link-to-system interface connects the two simulation levels through link abstraction model(s) (from [161]).

fic generation, radio resource allocation, mobility management, ICIC, and network planning. Accordingly, system-level simulators operate on time scales related to connection lifespans, whereas link-level simulators operate on time scales related to symbol, bit, or chip rates. Interfacing the two simulation levels then relies on the so-called *link-to-system interface*, which consists of link abstraction models derived from link-level simulation results over a representative set of channel conditions. These link abstraction models are usually implemented as look-up tables in practical system-level simulators. Overall, the link abstraction strategy enables both result accuracy and computational feasibility.

The VIENNA simulators [140, 141] provide an interesting example of a system-level simulator that employs link abstraction to evaluate the communication performance of 4G-LTE RANs. In the DL, the link-to-system interface consists of two abstraction models: (i) a link quality model, and (ii) a link performance model. Figure 3.6 illustrates the interaction between these two abstraction models and several model parameters. The link quality model characterizes the signal quality received by UEs through the post-equalization signal-to-interference-plus-noise ratio (SINR) determined by the power levels of the received signal, interference, and noise. Given the UE position, these quantities are influenced by the network layout (e.g., BS positions), large-scale radio channel effects (e.g., path loss and shadow fading), and small-scale fading. Then, the link performance model maps the SINR to block error rate (BLER) curves specific to the modulation and coding scheme (MCS) of 4G-LTE. In practice, these curves are derived from prior link-level simulations. The effective data throughput is finally computed from the transport block size and the BLER corresponding to the selected MCS. The throughput can also be obtained using the assigned bandwidth and the system-level spectral efficiency (SE).

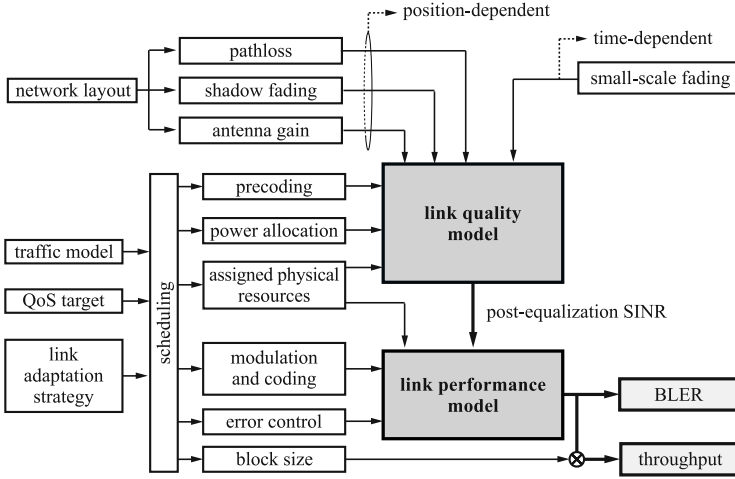


Fig. 3.6 The VIENNA system-level simulator consisting of two link abstraction models. First, the link quality model characterizes the signal quality received by the user equipment through the post-equalization signal-to-interference-plus-noise ratio (SINR). Second, the link performance model computes the effective throughput using the block error rate (BLER). Both abstraction models are affected by the base station scheduler based on the quality of service (QoS) target and link adaptation strategy (adapted from [141]).

Figure 3.6 also shows that both abstraction models are affected by the BS scheduler. Based on the QoS target and link adaptation strategy, this scheduler assigns physical resources, a precoding matrix, and a MCS to each active UE. To optimize network performance, some scheduling algorithms also rely on UE feedback regarding the radio link quality (e.g., reflecting the SINR).

Supported by extensive prior research, modeling the BS communication performance does not present a major research gap in the context of this thesis. Instead, the main challenge lies in selecting a modeling approach that provides sufficient accuracy to meet the goals of the thesis (e.g., informing decision-making at the country level) while remaining computationally feasible. In this regard, using the link abstraction strategy within a system-level simulator appears to be a suitable approach. The remaining challenge addressed in this thesis therefore concerns the practical implementation of a communication performance model and its integration with complementary BS models to create an integrated RAN model.

3.2.3 Base station power consumption models

Several models are proposed in the literature to assess the power consumption of various types and configurations of BSs. In general, these models consider multiple BS components, as illustrated by the block diagram from Auer et al. [131] shown in

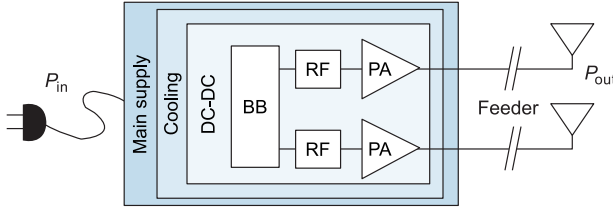


Fig. 3.7 Illustrative block diagram for a typical cellular base station, including antenna interfaces, feeders, amplifiers ("PA"), radio modules ("RF"), a baseband module ("BB"), power converters ("DC-DC"), cooling systems, and a main power supply. This representation aims to relate the transmit output power (" P_{out} ") to the input power consumption (" P_{in} ") within the evaluation framework presented in Figure 3.4 (from [131]).

Figure 3.7. This typical representation of a cellular BS includes antenna interfaces, feeders, amplifiers, radio modules, a baseband module, power converters, cooling systems, and a main power supply. In this review, two main categories of BS power models are identified: (i) top-down regression-based models, and (ii) bottom-up parametric models. Top-down models rely on empirical data about operating BSs, while bottom-up models are constructed from technical and theoretical knowledge about the design of individual BS components and related parameters.

Studies providing *top-down regression-based models* usually apply regression analysis to empirical measurements in order to derive a relationship between the power consumption of a BS (or its components) and a given explanatory variable, typically the data traffic volume. Top-down power models are proposed for 2G-GSM and 3G-UMTS BS components by Lorincz et al. [162], Gadze et al. [163] and Dahal et al. [164], and for 4G-LTE BS components by Lorincz et al. [165] and Capone et al. [166]. Since these models reflect the actual power consumption of BSs operating under realistic conditions, they are highly valuable for practical applications. However, existing studies providing top-down power models generally examine legacy technologies and, although they provide important insights, their quantitative results may be outdated for more recent technologies. Additionally, most of these models rely on hourly measurements, preventing them from capturing short-term variations in BS power consumption. Furthermore, the wide use of data traffic as the primary explanatory variable makes the models highly site-specific, thereby limiting their applicability to other BS locations.

In contrast, *bottom-up parametric models* represent the BS power consumption by aggregating detailed power models at the component and subcomponent levels. Since these models rely on multiple variables and parameters, they are typically used to optimize BS designs, communication protocols, scheduling strategies, etc. The first power models for single-band 4G-LTE BSs are provided by Deruyck et al. [167] and Auer et al. [131]. Then, building on the methodology developed in Desset et al. [168], Desset et al. [169] and Debaille et al. [170] propose flexible BS

power models derived from various technical data sources. These power models subsequently became very popular in the literature. Similar bottom-up models for single-band BSs are provided by Jung et al. [171] and Wang et al. [172]. Lorincz and Matijevic [135] also develop a simple power model for assessing multi-band BSs, but such models are rare in the literature. More advanced systems, such as BSs equipped with massive-MIMO, are prospectively modeled by Desset et al. [173], Björnson et al. [137], and Peesapati et al. [134], while mmWave BSs are investigated by Matalatala et al. [152], and THz systems are explored by Desset et al. [174]. Despite their high flexibility, existing bottom-up power models exhibit three main limitations. First, they generally lack validation of their chosen numerical parameter values against real-world data. Second, these models often fail to clearly specify their time scale (e.g., per radio frame or on an hourly basis), which complicates their integration with other BS models at the network level. Third, they rarely capture explicitly the nonlinear characteristics of the PAs.

Overall, the reviewed literature suggests that the average hourly power consumption of a traditional macrocell BS typically lies in the range of 500–1500 W per band, while that of a microcell BS is around 100–300 W per band. Prospective power models also predict an average power consumption around 200–800 W per band for massive-MIMO BSs, and < 10 W for next-generation picocell and femtocell BSs. However, most of these power consumption values remain weakly supported by empirical validation. Addressing this limitation motivates the development of an updated BS power consumption model in this thesis, based on real-world measurements. Furthermore, both top-down and bottom-up models indicate that the average BS power consumption can be decomposed in two parts: (i) a static power that remains constant over time, and (ii) a dynamic power that varies as a function of the data traffic volume or physical resource load. In general, dynamic power consumption is largely attributed to PAs and modeled linearly. Yet, it may actually be nonlinear due to PA characteristics, as well as when sleep modes and PSSs are implemented, as illustrated in [JP1] and [43, 44, 170, 175]. Therefore, an up-to-date model of BS power consumption should capture the nonlinear effects introduced by both PAs and PSSs.

3.2.4 Base station life-cycle environmental impact models

While BS power consumption models enable the assessment of operational electricity consumption of BSs, these models are insufficient to assess their environmental impacts throughout the life cycle. Assessing such impacts therefore requires dedicated BS life-cycle models that represent all relevant life-cycle stages, including electricity supply. In line with the LCA methodology (see Section 2.2.3), these models should encompass the production, distribution, use, and end-of-life (EoL) stages. An illustrative example a LCI model is provided in Figure 3.8 for a 5G-NR BS in China, as proposed by Ding et al. [176]. However, only a limited number of studies in the literature conduct a full LCA of BSs, and most of them focus pri-

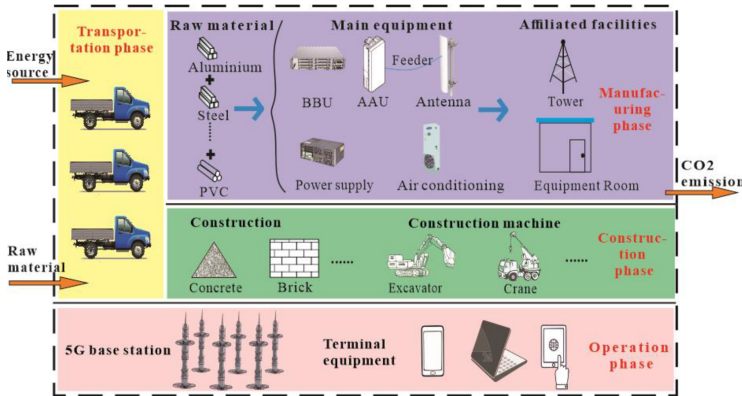


Fig. 3.8 Illustrative life cycle inventory model for assessing the CO₂ emissions from the life cycle of a 5G-NR base station in China. It represents multiple foreground processes in different life-cycle stages, including component manufacturing, transportation, site construction, and operations, but excludes end-of-life processes (from [176]).

marily – if not exclusively – on the climate change impact category. Accordingly, the rest of this section reviews carbon footprint assessments of BSs. Moreover, the focus is placed on the production stage, since impacts during the use stage are typically assessed using BS power consumption models combined with assumptions on emission factors for electricity generation.

Initial research efforts by Scharnhorst et al. [177, 178] and Faist Emmenegger et al. [179] estimated that the production of 2G-GSM and 3G-UMTS RANs ranges from 0.02 to 20 kgCO₂eq per Gbit of transmitted data. This wide range of impacts is primarily due to the "per Gbit" FU, which is highly sensitive to the assumed performance and lifetime of BS components. Using a different FU, Malmödin et al. [30] estimate the carbon footprint of producing RANs at 3.5 kgCO₂eq per subscription per year. Later, Bergmark [180] estimates 4 tCO₂eq for the production of one BS supporting 4G-LTE, or 0.5 kgCO₂eq per subscription per year. For 5G-NR BSs, Bieser et al. [36], Ding et al. [176], Stobbe et al. [37] and Aubet et al. [181] provide preliminary carbon footprint estimates ranging from 3 tCO₂eq for producing a single-band BS to over 10 tCO₂eq for a more advanced multi-band BS. Additional studies by Madon [182], Kallio et al. [183] and Guérid et al. [184] further investigate the life-cycle impacts of specific components used in modern BSs.

One issue when comparing these studies is their significantly differing scopes. For instance, some studies include the construction of a concrete terrace and an antenna tower, while others focus solely on communication-specific BS components. Excluding construction activities reveals that most impacts during the production stage stem from manufacturing electronic components, especially integrated circuits (ICs), and aluminum production, mainly used in BS component casings. An-

other issue when comparing these studies is the use of different FUs. For instance, some studies assess the impacts of an entire BS, while others normalize their results per bit of transferred data or per subscription. Tentatively harmonizing the results yields a carbon footprint of 3–30 tCO₂eq for producing one BS. Besides discrepancies in scope and FUs, this wide range of results is partly due to a lack of specific primary data for conducting the LCAs. As a result, most studies rely on generic background processes from databases as proxies for modeling BS components. This limitation underscores the need for more detailed LCAs of BSs based on specific empirical data (e.g., hardware teardowns). Furthermore, most existing studies assess only fixed BS configurations and therefore provide limited support for eco-design and optimization. Addressing this gap further motivates the development of a parametric BS life-cycle model in this thesis, enabling the comparison of alternative BS designs from an environmental perspective.

3.3 Research gaps

This chapter reviewed the state of the art in assessing the direct environmental impacts of mobile networks and in modeling RANs and their constituent BSs. The review outlined various approaches and perspectives for conducting these assessments and developing the associated models at different levels of abstraction. However, it also revealed several research gaps that currently prevent the literature from providing adequate support for decision-making toward environmental sustainability in mobile Internet access. Thus, this section summarizes these gaps to motivate the three research questions of this thesis.

A first major gap concerns the assessment of BS designs under realistic operating conditions. At the network level, previous assessments show that the energy efficiency of mobile networks has significantly improved over the past two decades. While this indicates the achievement of substantial efficiency gains, it does not explain which specific BS design choices are responsible for these gains, nor how much further improvement could be achieved in the future. In parallel, the literature proposes detailed BS models to assess communication performance, power consumption, and – to a lesser extent – life-cycle environmental impacts. However, these three aspects are usually examined separately, making it difficult to evaluate BS designs simultaneously in terms of communication and environmental performances. As a result, previous research offers limited insights into the development of next-generation BSs that are more efficient in terms of QoS and environmental impacts, particularly under typical traffic loads and deployment conditions. This gap motivates the following research question:

RQ2 *What BS designs are efficient in terms of QoS and direct environmental impacts under typical operating conditions?*

A second gap emerges at the network level, where most environmental assessments rely on relative performance indicators such as energy intensity metrics. While these metrics are useful for tracking efficiency trends over time, they do not adequately support decision-making toward absolute environmental sustainability. Several studies address this limitation by assessing the prospective energy consumption and GHG emissions of mobile networks at the country level. These prospective studies generally examine one baseline scenario and one or more alternative scenarios of RAN deployment strategies and data traffic demands to provide stakeholders with recommendations. However, none of the reviewed studies identifies scenarios that align with the SBTi trajectory set by the ITU. As a result, these studies provide limited guidance to MNOs and other stakeholders on deployment strategies and data traffic patterns that can achieve sustainable mobile Internet access at the country level. This gap motivates the following research question:

RQ3 *What RAN deployment strategy should be adopted by MNOs to transition toward environmental sustainability from an absolute perspective?*

Addressing the previous research questions requires overcoming another research gap: none of the reviewed RAN models or simulators integrates environmental impact assessment capabilities. This gap, in turn, prevents the consistent investigation of BS designs and RAN deployment strategies across different spatial and temporal scales. One potential approach to bridge this gap is to combine existing BS models at the network level. However, this solution is not straightforward because the communication performance, power consumption, and life-cycle environmental impacts of BSs are generally modeled separately, relying on different – sometimes incompatible – assumptions and modeling approaches. Moreover, while reliable communication performance models are widely available in the literature, power consumption models are either outdated or lack empirical validation, and no complete parametric LCA of BSs has been published yet. As a result, the following research question must be addressed prior to the other two:

RQ1 *How can a RAN be modeled to simultaneously assess its QoS and direct environmental impacts under given operating conditions?*

To address these three research questions, the rest of this thesis is organized into two parts. Part I addresses **RQ1** in Chapters 4, 5 and 6 by developing an integrated parametric model of RANs for simultaneously assessing QoS and life-cycle environmental impacts. Part II then applies the proposed integrated RAN model to address **RQ2** in Chapter 7 and **RQ3** in Chapter 8, adopting relative and absolute environmental perspectives, respectively. Throughout the thesis, special attention is also given to quantifying and analyzing uncertainty in order to improve the transparency and interpretability of the assessment results.

Summary

This chapter first reviews the state of the art on environmental impact assessments of mobile networks. These assessments generally focus on operational energy consumption and GHG emissions, and the results are primarily expressed as energy intensity metrics. While these relative metrics show efficiency improvements over time, they hide absolute impacts. Adopting an absolute perspective, prospective country-level studies assess mobile networks using scenarios on the supply and demand sides. However, none of the existing studies identifies RAN deployment strategies and data traffic patterns that align with the SBTi trajectory set by the ITU. The chapter then reviews the state of the art on integrated RAN models and simulators, as well as BS models for communication performance, power consumption, and life-cycle environmental impacts. At the network level, existing simulators do not directly integrate environmental impact assessment capabilities. At the BS level, reliable communication performance models are available, but power consumption models are either outdated or lack empirical validation, and no complete parametric LCA of BSs has yet been published. As a result, no existing parametric model enables the simultaneous assessment of QoS and direct environmental impacts of RANs under realistic operating conditions. Overall, this chapter motivates the development of an integrated parametric RAN model that can (i) support the evaluation of BS designs in terms of QoS and direct environmental impacts, and (ii) enable prospective assessments of RAN deployment strategies to support MNO decision-making toward environmental sustainability.

PART I

**Development of an
integrated parametric model
for radio access networks**

4

Methodology for developing the integrated radio access network model

This first part of the thesis addresses **RQ1** "*How can a RAN be modeled to simultaneously assess its QoS and direct environmental impacts under given operating conditions?*" Specifically, it develops an integrated parametric model for RANs providing mobile Internet access. This model builds upon the state-of-the-art RAN models reviewed in Chapter 3 and seeks to address the associated research gaps. In particular, unlike [JP1], it separates the modeling of QoS and energy consumption, thereby enabling greater flexibility and an explicit physics-based representation of RANs and its constituent BSs. Moreover, the proposed RAN model is structured across multiple time scales, combining short-term QoS assessment to capture user experience with long-term environmental impact assessment from a life-cycle perspective. Overall, this integrated model enables the techno-environmental assessment of RANs within the LCE framework established in this thesis.

Within Part I, this chapter introduces the general methodology for developing the integrated RAN model designed to simultaneously assess the QoS, energy consumption, and life-cycle environmental impacts. This methodology is subsequently applied in Chapter 5 to develop a parametric model for the power consumption of BSs, and in Chapter 6 to develop a parametric model for assessing the life-cycle environmental impacts of BSs. Despite its key role in the integrated RAN model, the parametric communication performance model for assessing network QoS is not presented in a dedicated chapter because it is not considered a novel contribution beyond the state of the art reviewed in Chapter 3.

In this chapter, Section 4.1 first defines the general goal and scope of the integrated RAN model. Section 4.2 then presents the general modeling approach, followed by an overview of the model in Section 4.3, including its practical implementation in a numerical simulation tool. To ensure applicability of the model in real-world contexts, Section 4.4 explains an approach for estimating the technological model parameters based on empirical data and quantifying the associated uncertainties. Finally, Section 4.5 defines the set of typical BS configurations used in the following chapters to generate illustrative results and to validate the proposed models against independent observations. This chapter combines and extends the methodologies introduced in [CP2] and [JP3].

4.1 Goal and scope

The goal of the proposed RAN model is to enable researchers, MNOs and network equipment manufacturers to assess and compare the techno-environmental performances of different RAN configurations, as well as to support the eco-design and optimization of next-generation BSs. This model is also intended for use in studies evaluating RANs at the country level, such as [JP1] and [36–38, 181]. The proposed RAN model focuses on the direct (or first-order) effects and excludes indirect (or higher-order) effects such as those enabled by mobile Internet access and the associated behavioral and structural effects at the macro level [66–69]. Nevertheless, this model can serve to assess the direct impacts of ICT services in studies that examine both their direct and indirect effects [70–72]. Furthermore, the bottom-up approach adopted by the proposed RAN model is designed to complement a top-down RAN assessments, e.g., based on AESA. Combined within a LCE framework, these two approaches can be used to inform decision-making and strategic planning toward more sustainable RAN deployment strategies.

One of the main innovations of the proposed RAN model is its ability to jointly assess the functional and environmental performances of RANs by simultaneously and parametrically assessing the QoS, energy consumption, and life-cycle environmental impacts. The *integrated* RAN model can then be used to optimize RAN and BS configurations with respect to environmental impacts and energy consumption, given requirements in terms of network coverage, data traffic capacity, physical resource load, etc. In order to facilitate reuse of the RAN model in future works, the modeling approach is based on four recommendations from the ITU: (i) Recommendations M.2135 [185] and M.2412 [186] on evaluating the QoS of 4G-LTE and 5G-NR RANs, respectively, (ii) Recommendation L.1310 [187] on evaluating the energy efficiency of telecommunication equipment, and (iii) Recommendation L.1410 [188] on applying the LCA methodology specifically to ICTs.

The technological scope of the RAN model is shown in Figure 4.1. Within the RAN, the system boundaries are limited to BS components dedicated to providing communication services, in particular, mobile Internet access. This includes the

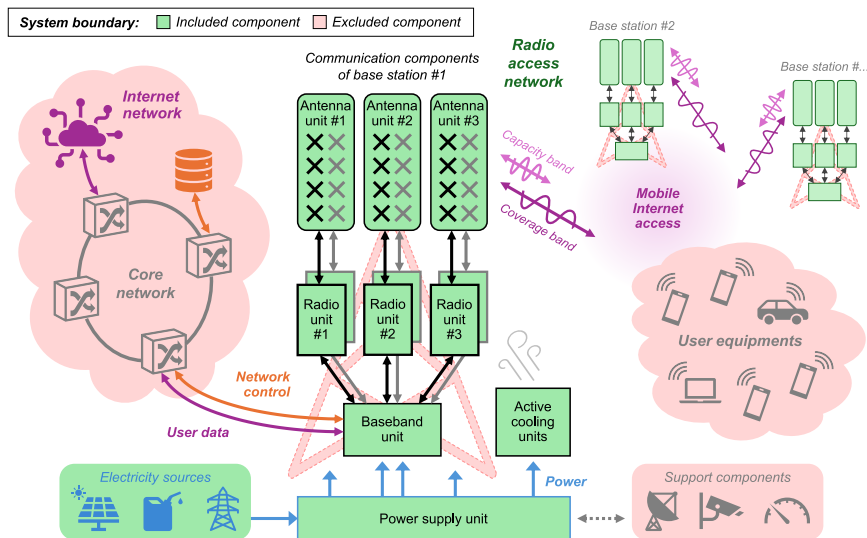


Fig. 4.1 Technological system boundary for the integrated network model. The scope includes the base station communication components dedicated to providing mobile Internet access within the radio access network. The electricity source is considered when assessing environmental impacts. The scope excludes the base station support components as well as the core network, the rest of the Internet network, data centers, and user equipments.

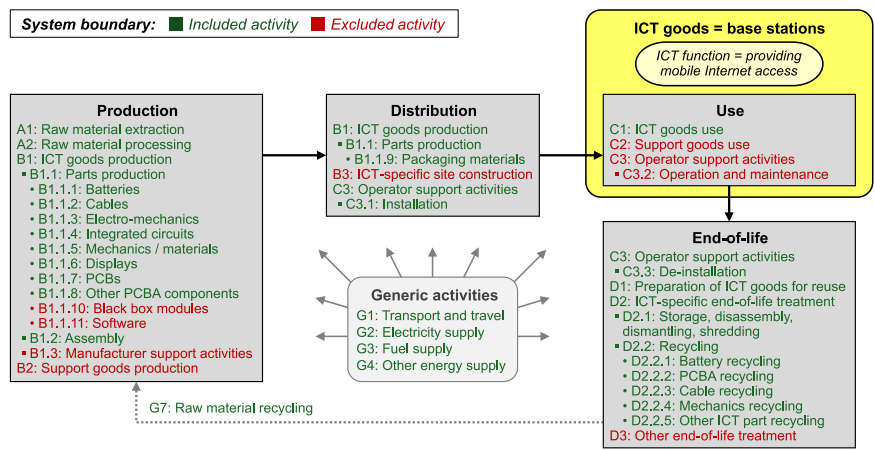


Fig. 4.2 Temporal system boundary for the integrated network model from a life-cycle perspective. Activities are grouped into four life-cycle stages plus a group of generic activities, according to the classification in ITU Recommendation L.1410 [188]. The base stations are the "information and communication technology (ICT) goods" under study, whose function is to provide mobile Internet access. The scope includes life-cycle activities of base stations, but excludes those of support goods and support activities.

communication components that handle user data signals, such as the digital and analog processing components, antennas, power supply, and cooling systems. To assess the environmental impacts of the RAN, the source of electrical power supply is also taken into account, including the electricity grid, photovoltaic (PV) systems, or diesel generators. Conversely, the model excludes BS support components such as security and monitoring systems, as well as site structures such as antenna towers and building. Since they are not part of the RAN, the mobile core network, the rest of the Internet, data centers, and UEs are also excluded. The model does, however, consider UE configuration parameters that affect network QoS, but does not assess energy consumption or environmental impacts of UEs. In the rest of this thesis, the term *network* refers specifically to the RAN.

The proposed network model focuses on up-to-date commercial BS architectures for outdoor RANs that support multiple sub-6 GHz frequency bands and communication protocols, including 4G-LTE and 5G-NR. The model solely considers the cellular network typology and not the cell-free typology. In this thesis, a *cell* is defined as one frequency band in one sector of one BS, such that, e.g., a BS with 2 frequency bands and 3 sectors contains 6 cells. The model includes large-cell (macro and micro) BSs that emit from 1 W to >100 W per cell. Yet, it excludes small-cell (pico and femto) BSs, emitting < 1 W per cell, as they are not primarily intended for deployment at sub-6 GHz and are better suited to indoor enterprise and private networks [24]. Typically, a macro BS covers three 120° sectors with directional antennas that emit ≥ 40 W per cell. On the other hand, a micro BS covers only one 360° sector with an omnidirectional antenna emitting < 40 W per cell.

Adopting a life-cycle perspective, Figure 4.2 shows the temporal scope of the network model with respect to four main life-cycle stages: production, distribution, use, and EoL. These four stages involve additional generic activities such as transportation and energy supply. The system boundary of the proposed network model includes life-cycle activities related to the communication-specific components of the BS, but excludes those of support goods and support activities. This definition of system boundaries is based on the ITU Recommendation L.1410 [188]. Accordingly, the BS is an "ICT good" that provides an ICT function, which can then be used as a building block to assess the environmental impacts of "ICT networks" and "ICT services". To assess these latter two "logical structures", the ITU recommends including additional ICT goods, such as core network equipment and customer-premise equipment, as well as support activities by MNOs and other ICT service providers, such as maintenance and business activities.

4.2 Modeling approach

A RAN is a complex system with heterogeneous macroscopic properties at the country level and diverse specific components and characteristics at the BS level. The RAN modeling approach described in this section aims to cope with these as-

pects. First, it outlines the general modeling principles. Then, it introduces and defines the concept of physical resource load, which plays an important role in the integrated network model. Lastly, the section explains how the BS architecture is represented in the model in terms of functional and physical components.

4.2.1 Modeling principles

The integrated network model is built around three bottom-up BS models: (i) a communication performance model, (ii) a power consumption model, and (iii) a life-cycle environmental impact model. The communication performance model assesses the QoS provided to UEs by the BS, the power model assesses the electrical energy consumption of the BS during the use stage, and the life-cycle model assesses the environmental impacts of the BS throughout its entire life cycle, from cradle to grave. These three BS models are integrated into a larger network model that also includes a traffic model for multiple BSs. The network-level model accounts for asynchronous BS usage and the associated inter-cell interference affecting the QoS. To simulate short-term traffic patterns, the traffic model generates rapid load fluctuations across the BSs and controls the three parametric BS models via the physical resource load (see Section 4.2.2). The average network usage is the input variable of the model, and the output results consist of the corresponding techno-environmental network assessments.

The integrated network model assesses small-scale cellular RANs (i.e., comprising 10–100 BSs). At this scale, the RAN is set to be homogeneous in terms of BS and UE densities, BS configurations, average data traffic per UE, radio propagation environment, etc. Specifically, the model assumes a uniform random spatial distribution of the UEs, as well as the regular deployment of a single BS configuration around a central BS of interest. Thus, the assessment of this central BS is considered representative of typical BSs in the network. To evaluate heterogeneous large-scale networks using the proposed network model (e.g., at the country level with 10^3 – 10^5 BSs), the assessments of different homogeneous network configurations must be aggregated, as with the E³F [131–134] (see Section 3.2.1). However, the network model is not designed to evaluate BSs at specific locations within a RAN, such as optimizing the placement and configuration of individual BSs.

The proposed model is capable of handling BS configurations that contain several frequency bands, each with different configurations in terms of bandwidth, communication protocol, transmit power, etc. The examined BSs may also implement different PSSs in the time, frequency, spatial, and power domains [44–46]. The network model uses short-term assessments to capture the rapid dynamics of data traffic and PSSs at the millisecond scale. Medium-term assessments then derive statistical network QoS and energy consumption over a longer time interval, typically one hour. Similar to the E³F [131], long-term assessments aggregate medium-term assessments to capture the slower dynamics of data traffic and PSSs over a full day or longer. Finally, environmental impact assessments cover the entire life cycle of

the BS, which has a typical lifetime of around ten years. As a result, assessing a RAN at the country level over one year requires aggregating small- to large-scale and short- to long-term network assessments.

Two modeling strategies are used together to model the network: the modular strategy and the parametric strategy [189]. The modular strategy involves modeling the network around reusable elements called modules, such as a specific BS component. Each specific module is first modeled separately, and then all modules are aggregated together to constitute the whole network. In addition, the parametric strategy aims to model the network – or its modules – through a set of network-related parameters. This approach requires identifying the key network parameters as well as the functions linking these parameters to the techno-environmental performances of the network. Often, this involves regression analysis. The combined modular and parametric modeling approach ensures that the network model is highly flexible and can be used to study the full range of BS configurations targeted in this thesis. This approach also allows for a detailed breakdown of performance and impacts by frequency band, BS component, and life-cycle stage.

The abstraction level of the network modules is intended to be as consistent as possible throughout the entire model. The goal is to minimize the "black-box" effect, thereby making the assessment results more explainable and actionable for engineering developments and eco-design. The parametric functions of all modules in the network model are first defined analytically, based on the known physical characteristics and behaviors of telecommunication systems, when possible. Then, the numerical values of the parameters are determined based on various up-to-date data sources. Separating the definition of parametric functions from the estimation of numerical parameters allows for updates to parameter values, making the network model more flexible and adaptable to future technological developments. The network assessment results are finally obtained through numerical model simulations, enabling the analysis of complex BS configurations.

4.2.2 Physical resource load

In the integrated network model, the *physical resource load* is a crucial aspect because it connects the network traffic model to the BS communication performance and power consumption models. Therefore, it plays a key role when assessing the QoS and energy consumption of the network. Since the use stage of the BS is directly modeled based on its energy consumption, the environmental impacts of the BS life cycle are also indirectly affected by the physical resource load through the BS power consumption model.

To properly define the physical resource load, it is important to briefly explain how 4G-LTE and 5G-NR protocols [12–14, 159, 160] utilize physical resources. Both protocols employ orthogonal frequency-division multiplexing (OFDM) to transmit and receive digital data bits on multiple orthogonal frequency carriers. With this

technique, the available physical resources are the time domain and a portion of the frequency spectrum. In the time domain, a radio frame is defined as a time interval of 10 ms, consisting of 10 subframes of 1 ms each. In the frequency domain, the available spectrum is bounded by the specified bandwidth around the carrier frequency. These physical resources are also divided into consecutive *symbols* in the time domain, and adjacent *subcarriers* in the frequency domain. This creates a *resource grid* in which one subcarrier within one symbol represents one *resource element (RE)*, as shown in Figure 4.3. The number of data bits carried per RE depends on the channel capacity, itself determined by the propagation conditions of radio channels between UEs and the BS.

Multi-antenna BSs exploit the spatial domain as an additional physical resource through MIMO techniques [12–14, 159, 160]. This resource is divided into parallel *spatial data layers*, each supporting a separate resource grid (see Figure 4.3). In this thesis, a spatial data layer¹ is defined as a physical channel able to convey up to one independent data stream. Therefore, the fixed number of spatial data layers corresponds to the maximum number of data streams that can be spatially multiplexed within a cell (for a single or multiple users). Under ideal radio propagation conditions, each spatial data layer conveys one dedicated data stream. Yet, under less favorable conditions, multiple spatial data layers may convey the same data stream to benefit from spatial diversity [12–14, 156]. In these conditions, the number of effective data streams is smaller than the number of spatial data layers. Spatial data layers also enable digital beamforming [12–14, 156]. Even without MIMO, the spatial domain acts as a physical resource because the same time-frequency resources can be reused across BSs and their sectors. With MIMO and beamforming, this reuse can be further exploited within a single sector.

In practice, REs are assigned to UEs in groups of subcarriers over multiple symbols [12–14, 159, 160]. In this thesis, a *physical resource unit (PRU)* is defined as a group of 168 REs contained in a frequency *resource block* of 12 subcarriers over a time *slot* of 14 symbols in a single spatial data layer². For sub-6 GHz frequencies, i.e., in frequency range 1 (FR1), the subcarrier spacing (SCS) is usually 15 kHz in

¹In 4G-LTE and 5G-NR, a layer is rather defined as an independent data stream that can be mapped to one or more antenna ports. In that case, the number of layers fluctuates depending on the radio channel quality. However, the proposed definition of spatial data layers in this thesis implies that their number remains constant over time, which aligns more closely with the concept of an *antenna port*. Note that an antenna port is a logical concept that does not directly correspond to physical antenna connectors.

²The 4G-LTE and 5G-NR protocols do not define slots and (physical) resource blocks in exactly the same way, which motivates the definition of a PRU to harmonize the terminology. For instance, a time slot contains 7 symbols in 4G-LTE and 14 symbols in 5G-NR. Additionally, the concept of a resource block is only defined in the frequency domain in 5G-NR, whereas in 4G-LTE, it corresponds to all REs over 12 subcarriers and 7 symbols, also called a physical resource block. Since resources are allocated in pairs of consecutive physical resource blocks in 4G-LTE, this is compatible with the proposed PRU definition.

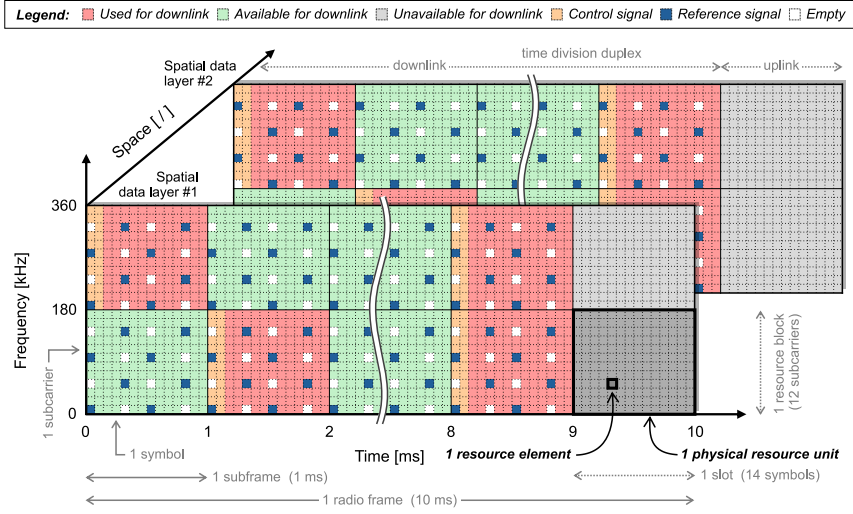


Fig. 4.3 Physical resources available for transmitting and receiving digital data in a cell. The time, frequency, and spatial domains are organized into a resource grid consisting of symbols, subcarriers, and spatial data layers. Resources are split between the downlink and the uplink. A physical resource unit is a group of resource elements assigned to users by the base station. Resource elements also transmit control or reference signals, and some remain empty to avoid interfering with reference signals from parallel spatial layers.

both 4G-LTE and 5G-NR, with a symbol duration of $\sim 71 \mu\text{s}$ (including the cyclic prefix). Thus, a PRU occupies 180 kHz for 1 ms. Still in FR1, the 5G-NR protocol offers another SCS of 30 kHz for symbols lasting only $\sim 35 \mu\text{s}$, resulting in PRUs of 360 kHz over 0.5 ms. In 5G-NR, these two SCS options correspond to numerologies 0 and 1, respectively. Consequently, a subframe comprises one time slot with numerology 0 and two time slots with numerology 1. Yet, the number of PRUs and REs remains constant within a subframe because, for a given bandwidth, doubling the number of slots results in half of the number of resource blocks.

Under normal operating conditions, a BS should not continuously use all of its available physical resources. Otherwise, it would be fully saturated all the time, resulting in heavy data traffic congestion [131, 166, 190]. Specifically, the physical resource load (also referred to as the *load*) indicates the actual utilization level of physical resources in a cell, ranging from 0 to 1 [131, 169, 170]. In this thesis, the load represents the number of occupied PRUs in each cell, which is used to model both the communication performance and power consumption of the BSs. Regarding communication performance, the load is combined with the BS configuration and the system-level SE to determine the actual data throughput of the BS. In particular, the system-level SE reflects the radio channel quality and accounts for the share of REs available per PRU to carry useful data. Since some REs are

needed to carry reference or control signals while others must remain empty, there are < 168 REs available per PRU to carry useful data (see Figure 4.3). Regarding power consumption, the load captures the dynamic BS power consumption, which is primarily driven by the highly load-dependent PAs (see Chapter 5).

In the proposed network model, the load is calculated solely in the DL because the examined QoS metrics focus on the DL (see Section 4.3.4), and because the PAs are only used in the DL (see Section 4.2.3). Accordingly, the physical resource load of subframe t_{sf} in layer l in a cell with N_L spatial data layers is defined as

$$x[l, t_{sf}] = \begin{cases} \frac{B_{DL}^{used}[l, t_{sf}]}{B_{DL}^{avail}[l, t_{sf}]} & \text{if } B_{DL}^{avail}[l, t_{sf}] > 0 \\ 0 & \text{if } B_{DL}^{avail}[l, t_{sf}] = 0 \end{cases}, \quad (4.1)$$

where $B_{DL}^{used}[l, t_{sf}]$ and $B_{DL}^{avail}[l, t_{sf}]$ are respectively the used bandwidth for DL and available bandwidth for DL. In frequency division duplex (FDD), only half of the frequency bandwidth is available for DL at any given time. Yet, in FDD, the bandwidth B is typically defined as the bandwidth available for DL only, such that $B_{DL}^{avail}[l, t_{sf}] = B$. In time division duplex (TDD), the entire bandwidth B is available for DL, but only during DL subframes, as shown in Figure 4.3. Conversely, there is no DL during subframes dedicated to UL. Therefore, in TDD, $B_{DL}^{avail}[l, t_{sf}] = B$ in DL subframes, and $x[l, t_{sf}] = 0$ during UL subframes.

In both duplex schemes, the average physical resource load of a cell at time t over a period containing N_{sf} subframes is defined as the time average of the per-subframe loads of all spatial layers of the cell during the DL subframes of that period. The average physical resource load is then calculated as

$$\bar{x}[t] = \frac{1}{\tau_{DL} N_{sf}} \sum_{t_{sf}=t}^{t+N_{sf}-1} \left(\frac{1}{N_L} \sum_{l=1}^{N_L} x[l, t_{sf}] \right), \quad (4.2)$$

where τ_{DL} is the DL time ratio, such that $\tau_{DL} = 1$ in FDD and $\tau_{DL} < 1$ in TDD. To calculate the hourly average load profile for one day, t must correspond to each hour of the day, and $N_{sf} = 3.6 \times 10^6$ subframes.

4.2.3 Base station architecture

The BS is the main building block of the integrated network model. Within the mobile network, the BS handles and processes user data signals between the mobile core network and the UEs. Upstream from the BS, digital data traffic is usually transferred over wires, while between the BS and mobile UEs, data is transmitted over radio waves. Data traffic can also be transmitted in two directions. The DL data traffic is transmitted from the BS to the UEs, while the UL data traffic is received from the UEs by the BS and then transferred to the core network. To as-

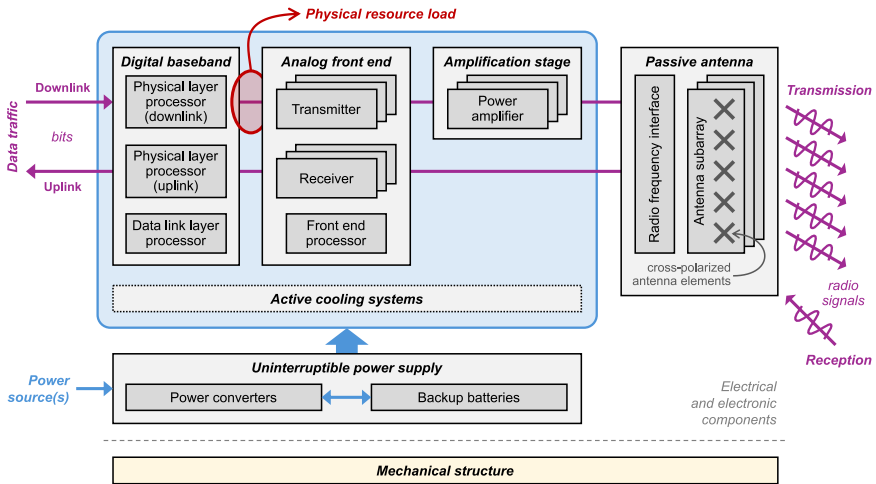


Fig. 4.4 Functional base station architecture representation for one cell, decomposed into components and subcomponents. The digital baseband, analog front end, amplification stage, and active cooling systems consume electricity supplied by the uninterruptible power supply, whereas the passive antenna and mechanical structure do not require a power supply. The base station converts user data from digital bits to radio signals in downlink, and vice versa in uplink. The physical resource load is only defined in the downlink.

sess both the BS energy consumption and environmental impacts, the proposed network model relies on two representations of the BS architecture. The first representation decomposes the BS architecture into functional components, and the second decomposes it into physical components. These two modular representations enable each component to be modeled independently while maintaining a clear view of how they interact with each other.

4.2.3.1 Functional base station components

The functional representation of the BS architecture emphasizes the functions and operations performed by the BS, regardless of their physical implementation (although the two are linked). This functional architecture is organized into seven main components, each of which is responsible for a specific set of operations and/or functions in the communication chain of the BS. Figure 4.4 illustrates these functional components and their subcomponents for one cell in a BS. The figure also indicates the DL and UL data traffic paths and identifies the active functional components that require an electrical power supply.

Five of the functional BS components are responsible for active electrical and electronic functions and operations.

- The **digital baseband (DBB)** performs all digital baseband signal processing

and communication protocol tasks, serving as the interface between the core network and the rest of the BS. It is subdivided into two physical layer processors (for DL and UL) that handle modulation/demodulation, channel coding/decoding, and digital precoding and/or beamforming [137, 169–174], and a data link layer processor responsible for data link functions such as physical resource scheduling and retransmission protocols [191]. The complexity of the DBB mainly depends on the total BS capacity, which depends on the number of sectors N_S , the number of frequency bands N_B , the bandwidth B of these bands, their number N_L of spatial data layers, etc.

- The **analog front end (AFE)** includes transmitters that perform digital-to-analog conversion, frequency up-conversion, as well as signal pre-driving to the PAs. It also includes receivers that perform low-noise amplification of signals from the antenna, frequency down-conversion and analog-to-digital conversion. A transmitter-receiver pair is referred to as a transceiver (TRX). These subcomponents act as bridges between the digital baseband and the analog RF domains. The front end processor controls and monitors the AFE circuitry, including calibration, gain control, frequency synthesis, and clock generation [137, 169–174]. Several TRXs are often used in parallel within the same cell to support MIMO. Typically, there is an equal number of transmitters N_{TX} and receivers N_{RX} per cell, such that $N_{TX} = N_{RX} = N_{TRX}$, where $N_{TRX} \geq N_L$ is the number of TRXs. When $N_{TRX} > N_L$, several TRXs convey the same spatial data layer, enabling adaptive beamforming (ABF).
- The **amplification stage (AS)** is dedicated to DL and boosts the RF analog signals generated by the AFE to the output power required for over-the-air transmission, while maintaining linearity and minimizing signal distortion. Given its high power consumption and heat generation, the AS is a critical component [137, 169–174]. The AS contains a number N_{PA} of PAs, each of which can output a maximum power of P_{TX}^{max} . Normally, there are as many PAs in the AS as there are transmitters in the AFE, such that $N_{PA} = N_{TRX}$.
- The **active cooling systems (ACSs)** such as fans are used to dissipate heat generated by active electrical and electronic components [137, 169–174].
- The **uninterruptible power supply (UPS)** delivers stable electrical power to all active components of the BS. It integrates both alternating current (AC) to direct current (DC) and DC/DC power converters to adapt input power to the different voltage levels required. It also integrates backup batteries to ensure continuous operation during power outages [137, 169–174, 192, 193].

An additional component handles passive electrical and electronic operations:

- The **passive antenna** provides the interface between the active RF circuitry and the radio propagation environment. It converts amplified electrical sig-

nals into electromagnetic waves for transmission (TX), and vice versa for reception (RX). This component includes an RF interface composed of filters, duplexers, combiners, and phase shifters for signal routing and conditioning. It may also include regular arrangement of antenna subarrays composed of multiple antenna elements (AEs) to form specific radiation patterns [194, 195]. This typically results in a maximum total antenna gain $G_{TX}^{max} > 0$ dBi.

The last component handles mechanical functions for the BS:

- The **mechanical structure** encompass the structural frame, protective housing, and mounting hardware of the BS. It ensures mechanical stability, environmental protection, and integration of all components, while also contributing to passive heat dissipation.

The number of functional components and subcomponents in a BS may vary depending on the BS configuration. Notably, the total number of AFEs, ASs, and active antennas is affected by the number of cells supported by the BS. Chapter 5 further explains how the BS configuration affects its functional composition.

4.2.3.2 Physical base station components

The physical representation of the BS architecture describes how the functional components are implemented in physical hardware units. In this representation, one functional component can be implemented by more than one physical component, and one physical component can implement more than one function. Different physical component designs can also perform the same function.

Large-cell BSs are typically made up of six types of physical components.

- The **baseband unit (BBU)** primarily performs the DBB functions. It usually contains a set of boards that handle the data link and physical layers of communication protocols [191] such as 4G-LTE and 5G-NR. In general, these boards are shared by all cells of the BS, though specific boards are often optimized for a particular protocol. The BBU also contains ancillary subcomponents responsible for cooling and power supply.
- The **radio unit (RU)** contains the AFE, the PAs, and part of the RF interface (typically the filters, duplexers and combiners) for one cell. RUs often support different communication protocols, but they are usually optimized for a particular one. RUs can be classified into subtypes according to two aspects. The first aspect is their total output power:
 - a macrocell RU emits from 40 W to > 100 W per cell,
 - and a microcell RU emits 1–40 W per cell.

The second aspect is the physical location of the RU on the BS site:

- a radio frequency unit (RFU) is installed in the BS cabinet near the BBU,

- and a remote radio unit (RRU) is installed outdoors closer to the passive antenna to reduce signal power loss in the connecting cables.

RFUs require ACSs to dissipate the heat they generate in the BS cabinet, whereas passive cooling is often sufficient for RRUs as they are located outdoors. In general, a RU is dedicated to a single cell of the BS. Yet, dual-band and triple-band RUs also exist and combine the RU functions of two or three frequency bands into a single unit. This primarily aims to save space and simplify on-site installation, while potentially reducing power consumption. Some single-band RUs (typically RFUs) also combine the RU functions for all sectors within a specific frequency band.

- The **antenna unit (AU)** consists of the passive antenna, including part of the RF interface (typically the passive phase-shifters). A single AU usually covers a unique sector and consists of one or more two-dimensional antenna arrays, each of which handles a dedicated frequency band. Each antenna array contains multiple AEs (typically cross-polarized) arranged in rows and columns and split into subarrays. Antennas with multiple subarrays are required to implement ABF [194, 195].
- The **active antenna unit (AAU)** is a special physical BS component that combines the RRU and AU for one cell into a single physical unit. This recent type of component further saves space at the BS site and eliminates the need for external cables to transmit the amplified RF signal to the antenna, thereby reducing signal power losses. The AAU is typically used to implement massive-MIMO in 5G-NR BSs.
- The **power supply unit (PSU)** performs the power conversion and distribution of the UPS for the entire BS. It supplies uninterruptible electrical power to the BBU and all RUs and AAUs of the BS. Thus, it comprises several power converters, a distribution panel, and backup batteries to ensure continuous operation of the BS, even during power outages.
- The **external cables** connect the physical BS components together [196]. There are three types of external cables:
 - optical fibers are data cables used to transfer digital signals between the physical layer boards in the BBU and the corresponding RUs,
 - coaxial cables are data cables used to transfer the amplified analog signals between each RU and the corresponding AU,
 - and power cables carry the electrical power between the PSU and all other active physical components.

Since an AAU combines a RU with an AU, this type of physical components does not require external coaxial cables.

The number of physical components and subcomponents in a BS may vary depending on the BS configuration. Notably, the total number of RUs, AUs (or AAUs), and external cables is affected by the number of cells supported by the BS. Chapters 5 and 6 further explain how the BS configuration affects its physical composition. Unlike large-cell BSs, small-cell (pico and femto) BSs are designed to be very compact and integrated into a single physical unit. Therefore, their architecture is fundamentally different from that of large-cell BSs, which also justifies their exclusion from the scope of the proposed model.

4.3 Model overview

This section provides an overview of the proposed integrated model designed to assess small-scale homogeneous RANs across various configurations and operating conditions. The section first presents the general structure of the model and then introduces its different time scales. Next, it defines the complete set of input variables and output results. Lastly, the section describes the practical implementation of the proposed model in a numerical simulation tool.

4.3.1 General structure

The general structure of the integrated network model is organized into two levels, as illustrated in Figure 4.5. At the network level, the model includes a traffic model that simulates short-term data traffic patterns across multiple BSs (typically 10–100), accounting for asynchronous cell activity and inter-cell interference. At the BS level, the model comprises three parametric BS models: (i) a communication performance model, (ii) a power consumption model, and (iii) a life-cycle environmental impact model. The communication performance model assesses the QoS provided by the central BS of interest, the power consumption model assesses its electrical energy consumption during the use stage, and the life-cycle model assesses the BS environmental impacts throughout its entire life cycle. In this thesis, Chapter 5 describes the BS power consumption model and Chapter 6 details the BS life-cycle environmental impact model. However, the BS communication performance model is not presented in this thesis because it is not considered a novel contribution compared to state-of-the-art models. Specifically, this model employs the conventional link abstraction strategy and is largely inspired by the system-level VIENNA simulator [140, 141] (see Section 3.2.2).

The *input variable* of the model is the network usage, which is expressed as the average hourly data traffic volume per user. Through the traffic model, this variable determines the physical resource load in each cell of the network. Next, the physical resource load of cells in the central BS of interest is used to model both its QoS and power consumption. The BS power model then feeds into the BS life-cycle model to simulate the use stage. The *output results* of the model are the assessments

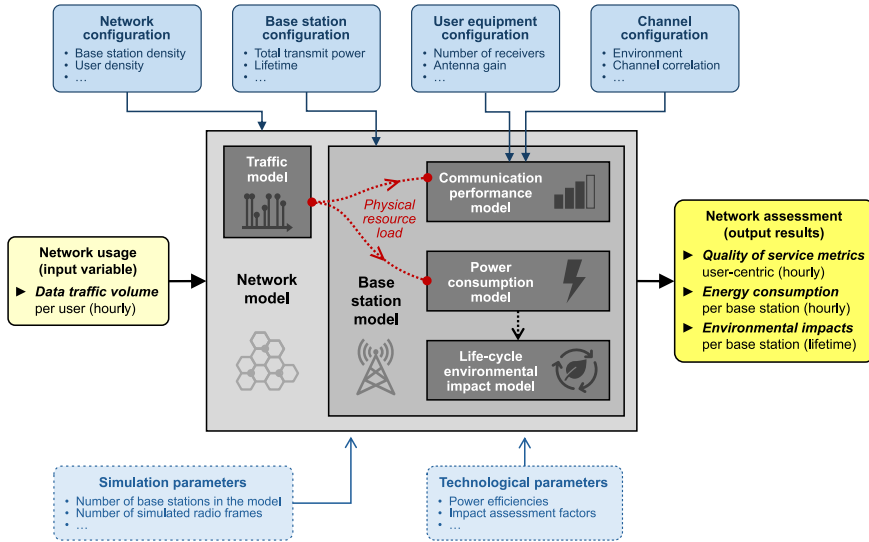


Fig. 4.5 General structure of the integrated network model, including a network traffic model and three parametric models for the base station: a communication performance model, a power consumption model and a life-cycle environmental impact model. The physical resource load connects the network traffic model to the communication and power models. The input variable is the network usage and the configuration variables represent the network, base station, user equipment, and channel configurations. Output results are the network assessments in terms of quality of service metrics, energy consumption, and environmental impacts. Technological and simulation parameters also affect the model.

of hourly user-centric QoS metrics, the hourly energy consumption of the entire BS, and the life-cycle environmental impacts of the BS over its whole lifetime. When using the model, model users can set a single network usage or a network usage profile comprising multiple usage levels, e.g., a daily usage profile. They can then adapt the obtained output results to their specific needs, e.g., by multiplying the energy consumption of the BS by the total number of BSs in the entire (homogeneous) network under study, or by allocating the total life-cycle environmental impacts of the BS per year, per day, or per hour, depending on the scope of their study.

The integrated network model is also affected by four sets of *configuration variables*: (i) network configuration variables, (ii) BS configuration variables, (iii) UE configuration variables, and (iv) channel configuration variables. The BS configuration variables represent the BS features that can be configured by MNOs (e.g., the total transmit power per cell), while the UE configuration variables represent the features of UEs utilized by the network users (e.g., their number of receivers). The network configuration variables defines the general network structure (e.g., the BS density) and the channel configuration variables describes the conditions of

radio signal propagation (e.g., the radio propagation environment). Network configuration variables apply to the entire network model, BS configuration variables apply to the three parametric models of the BS, and UE and channel configuration variables apply only to the communication performance model of the BS.

Furthermore, the integrated network model depends on two sets of *model parameters*: (i) technological parameters, and (ii) simulation parameters. Technological parameters represent model parameters that cannot be directly controlled by MNOs or UEs (e.g., the power efficiencies of BS components, the radio channel losses in a given environment, or the environmental impact factors of electricity from a specific source). Numerical values of these parameters are estimated using various up-to-date data sources, as explained in Section 4.4. These estimates are provided in Chapters 5 and 6 for the corresponding parts of the model. However, these numerical values may need to be updated in future works to take into account technological developments. Finally, simulation parameters define how the network model is simulated (e.g., by setting the total number of BSs considered in the network, or the number of simulated radio frames). These parameters primarily affect the simulation time and the precision of the output results.

4.3.2 Time scales

The integrated network model considers multiple time scales to capture the dynamics of various network behaviors. These time scales also provide the appropriate temporal perspectives for assessing the different techno-environmental performances of the network. Accordingly, seven time scales are defined.

- The **instantaneous** time scale, indicated by the continuous time t , captures the rapid oscillations of the OFDM signal envelope at the carrier frequency. Quantities varying at this time scale are expressed as $q(t)$.
- The **per-symbol** time scale, indicated by the discrete time t_s , corresponds to a time period of one symbol, typically $\sim 71 \mu\text{s}$ (or $\sim 35 \mu\text{s}$ with numerology 1 in 5G-NR). Quantities varying at this time scale are expressed as $q[t_s]$.
- The **per-subframe** time scale, indicated by the discrete time t_{sf} , corresponds to a time period of one subframe, or 1 ms. Quantities varying at this time scale are expressed as $q[t_{sf}]$.
- The **multi-frame** time scale, indicated by the discrete time t_f , corresponds to a time period of several radio frames. Quantities varying at this time scale are expressed as $q[t_f]$. In simulations, the duration of this time period can be configured using the parameter N_{sf} , which sets the number of subframes within that period. By default, this duration is 20 ms, corresponding to the typical periodicity of synchronization signals in 4G-LTE and 5G-NR.
- The **hourly** time scale, indicated by the discrete time t_h , corresponds to a

one-hour time period T_h containing 3.6×10^6 subframes. Quantities varying at this time scale are expressed as $q[t_h]$.

- The **daily** time scale corresponds to a one-day time period and refers to the time duration $T_{day} = 24$ hours.
- The **lifetime** scale corresponds to the duration of the BS lifetime, typically 10 years. The BS lifetime is configured using the variable T_{life} in years.

The network model is designed to study the effects of hour-by-hour fluctuations in network usage on QoS and power consumption, as well as to compare network performances during busy and off-peak hours. Therefore, the input model variable representing the network usage is defined at the *hourly* time scale, as well as most output network assessment results, e.g., the average DL throughput per user and the BS energy consumption. The use of one-hour intervals is motivated by their typical use by MNOs to monitor and optimize their BSs.

To compute the hourly assessment results, short-term assessments are first performed at the *per-subframe* time scale. This captures the rapid fluctuations in data traffic and subsequent nonlinear power consumption. Since 4G-LTE and 5G-NR BSs also cope with data traffic at this time scale, short-term assessments reflect how UEs perceive the QoS provided by the network (e.g., through their DL throughput). Then, medium-term assessment results are derived at the *hourly* time scale from a statistical analysis of the short-term results (e.g., the average DL throughput per user). In between, the *multi-frame* time scale is used for intermediate calculations to avoid simulating every subframe within an hour. Next, long-term network assessments can be performed at the *daily* time scale by aggregating medium-term assessment results. Finally, assessing the environmental impacts of the network requires adopting a life-cycle perspective at the scale of the entire BS *lifetime*.

Furthermore, the *per-symbol* and *instantaneous* time scales are used to model the PA power consumption, as it capture variations of the per-symbol PA output power, as well as variations in PA power efficiency due to oscillations of the OFDM signal envelope. PSSs may also be implemented at different time scales [44–46, 170]. In the proposed model, dynamic PSSs are applied at the *multi-frame* time scale and fixed PSSs at the *hourly* time scale. This means that the activation or deactivation of BS components remains the same for typically 20 ms with dynamic PSSs and for one hour with fixed PSSs. This distinction is important for studying how the performance of PSSs differs depending on their time response. Another interest of the *hourly* time scale is to enable comparisons of network assessment results with real-world network performances as observed by MNOs.

4.3.3 Input and configuration variables

The input variable of the integrated network model is the average hourly data traffic volume (DL+UL) per user, denoted by $\bar{v}_{UE}[t_h]$, and expressed in megabytes

per UE (MB/UE). The model is also affected by four sets of configuration variables representing configurations of system features: (i) network configuration variables, denoted by φ_{net} , (ii) BS configuration variables, denoted by φ_{BS} , (iii) UE configuration variables, denoted by φ_{UE} , and (iv) channel configuration variables, denoted by φ_{chan} . Unlike the input network usage variable, which varies on an hourly basis, the configuration variables are assumed to remain constant over time. Table 4.1 provides the complete sets of model variables. These variables were selected to represent key aspects of RANs, ensuring that the proposed model is flexible and can be consistently used in future works.

Since the proposed model allows for the assessment of multi-band BS, some variables must be defined for each frequency band, while others are defined once for the entire network. Similarly, some variables must be defined per UE category, assuming heterogeneity in UE configurations. This aspect is identified as the *scope* of variables in Table 4.1. Configuration variables also fall into three categories: continuous numerical, discrete numerical, and categorical. The variable *domain* specifies the set of admissible values for each variable. The domain indicates a numerical range for continuous variables, a set or range of integer values for discrete variables, and the list of allowed categories for categorical variables.

Table 4.1 also identifies which configuration variables affect which part of the model. For instance, the BS density affects both the network traffic model and the BS communication performance model, while the UE density only affects the traffic model. Moreover, the number of sectors affects the three models of the BS, whereas the share of indoor UEs only affects the communication performance model, the PA architecture only affects the power consumption model, and the source of electricity only affects the model of life-cycle environmental impacts. Indirectly, all variables affecting the power model also influence the environmental impact model because the former feeds into the latter. The specific use of configuration variables in the power and life-cycle models is detailed in Chapters 5 and 6, respectively.

4.3.4 Output results

The output results of the integrated network model are the network assessments calculated by the three parametric BS models and summarized in Table 4.2.

The BS communication performance model assesses three QoS metrics on an hourly basis. The first QoS metric is the average DL throughput per user $\bar{r}_{UE}[t_h]$, defined as the average per-user DL throughput when UEs are active (i.e., receiving DL data). This metric is expressed in megabits per second per UE (Mbps/UE). The second QoS metric is the DL network coverage $\zeta_{net}[t_h]$, defined as the ratio of UEs able to receive DL data to the total number of UEs attempting to communicate with the network. This metric is a dimensionless quantity. The third QoS metric is the average physical resource load of the network $\bar{x}_{net}[t_h]$, which reflects the probability of network congestion and the subsequent traffic latency. It is also a dimensionless quantity. The three QoS metrics are considered user-centric since

Table 4.1 Complete set of variables for the integrated network model

Scope ^a	Description	Symbol	Unit ^b	Domain	Default	Affected models ^c		
						Tra.	Com.	Pow. Imp.
Network usage variable								
Net.	Hourly data traffic volume per UE	$\overline{v}_{UE}[t_h]$	MB/UE	0–500	varying	input variable of the network model		
Network configuration variables φ_{net}								
Net.	BS density	ρ_{BS}	BS/km ²	0.01–10 ⁴	0.33	x	x	
Net.	UE density	ρ_{UE}	UE/km ²	0–10 ⁶	250	x		
Base station configuration variables φ_{BS}								
Net.	Antenna height	h_{BS}	m	10–50	25		x	x
Net.	Number of sectors	N_S	#	1,3	3		x	x
Net.	Number of bands	N_B	#	1–7	1		x	x
Net.	Fixed PSS	κ_{fPSS}	–	no, band sleep, layer sleep	no		x	x
Net.	Dynamic PSS	κ_{dPSS}	–	no, band sleep, layer sleep	no		x	x
Net.	Full-load backup battery duration	T_{backup}	hours	0–3	0.25			x
Net.	International distribution distance	d_{inter}	km	0–4×10 ⁴	2×10 ⁴			x
Net.	Local distribution distance	d_{local}	km	0–10 ³	500			x
Net.	BS lifetime	T_{life}	years	0–20	10			x
Net.	Electricity source	κ_{elec}	–	grid,PV, diesel gen.	grid			x
Net.	Waste management route	κ_{waste}	–	disposal, recycling	disposal			x
Band	Communication protocol	κ_{prot}	–	4G-LTE, 5G-NR, custom	4G-LTE		x	x
Band	Duplex scheme	κ_{duplex}	–	FDD,TDD	FDD		x	x
Band	Carrier frequency	f	GHz	0.5–6	0.8		x	x
Band	Bandwidth	B	MHz	1–100	10		x	x
Band	Number of spatial data layers	N_L	#	1,2,4,8	2		x	x
Band	Number of TRXs	N_{TRX}	#	1,2,4,8, 16,32,64	2		x	x
Band	Maximum transmit power per PA	P_{TX}^{max}	W	1–80	40		x	x

^a "Net." variables are defined once for the entire network, and "Band" (resp. "Cat.") variables are defined for each frequency band (resp. user equipment category).

^b "/" = a dimensionless quantity, and "–" = *not applicable* for categorical variables.

^c "Tra." = traffic model, "Com." = communication performance model, "Pow." = power consumption model, and "Imp." = life-cycle environmental impact model.

Table 4.1 Complete set of variables for the integrated network model (*continued*)

Scope ^a	Description	Symbol	Unit ^b	Domain	Default	Affected models ^c		
						Tra.	Com.	Pow. Imp.
Band	Full load transmit power per PA	P_{TX}^{full}	W	1–80	40	x	x	
Band	Ref. signals boost	β_{RS}	dB	0–6	3	x		
Band	Horizontal HPBW	ψ_{hHPBW}	°	30–360	65	x		
Band	Maximum total antenna gain	G_{TX}^{max}	dBi	0–25	16	x		x
Band	ABF capability	κ_{ABF}	–	without, with	without	x		x
Band	Number of antenna polarizations	N_{pol}	#	1,2	2	x		x
Band	Relative position of RUs between BBU and AUs	δ_{cable}	/	0–1	0.8	x		x
Band	RU type	κ_{RU}	–	RFU,RRU, AAU	RRU		x	x
Band	PA architecture	$\kappa_{PA,arch}$	–	Class-AB, Doherty, ET,APT, custom	Doherty		x	
Band	PA technology	$\kappa_{PA,tech}$	–	LDMOS, GaN, GaAs, custom	LDMOS		x	
<i>User equipment configuration variables φ_{UE}</i>								
Net.	Antenna height	h_{UE}	m	1–20	1.5	x		
Net.	Indoor share	$\delta_{UE,in}$	/	0–1	0.5	x		
Cat.	Category share	$\delta_{UE,cat}$	/	0–1	1	x		
Cat.	Number of RXs	$N_{RX,UE}$	#	1,2,4,6,8	1	x		
Cat.	Total antenna gain	$G_{RX,UE}$	dBi	0–10	0	x		
<i>Channel configuration variables φ_{chan}</i>								
Net.	Radio propagation environment	κ_{envi}	–	urban, suburban, Rural	suburban	x		
Net.	Outdoor-to-indoor path loss range	L_{O2I}^{range}	dB	0–100	[10,40]	x		
Net.	Spatial layer decorrelation probability	δ_{decorr}	/	0–1	0.5	x		
Net.	Effective SINR mapping exponent	α_{eff}	/	0–1	0.7	x		

^a "Net." variables are defined once for the entire network, and "Band" (resp. "Cat.") variables are defined for each frequency band (resp. user equipment category).

^b "/" = a dimensionless quantity, and "–" = *not applicable* for categorical variables.

^c "Tra." = traffic model, "Com." = communication performance model, "Pow." = power consumption model, and "Imp." = life-cycle environmental impact model.

Table 4.2 Output assessment results from the integrated network model

Description	Perspective ^a	Time scale	Symbol	Unit ^b
<i>Quality of service assessment</i>				
Average downlink throughput	UE	Hourly	$\bar{r}_{UE}[t_h]$	Mbps/UE
Downlink coverage	Network	Hourly	$\zeta_{net}[t_h]$	/
Average physical resource load	Network	Hourly	$\bar{x}_{net}[t_h]$	/
<i>Energy consumption assessment</i>				
Total energy consumption	BS	Hourly	$E_{BS}[t_h]$	Wh/BS
<i>Environmental impact assessment</i>				
Total life-cycle environmental impacts	BS	Lifetime	I_{BS}	impacts/BS

^a The "network" perspective is approximated by the central base station in the model.

^b "/" = a dimensionless quantity, and "impact" units differ for each impact category.

they capture the service that users actually perceive, rather than, e.g., the total BS throughput. These metrics focus on the DL because MNOs prioritize this direction when deploying RANs. One reason is that most mobile data traffic occurs on the DL (approximately 90%, see Appendix A.2), thereby constituting the main design constraint for current RANs. In future work, it would be worthwhile to include the UL in QoS metrics, particularly with regard to coverage.

Next, the BS power consumption model assesses the hourly energy consumption per BS, denoted by $E_{BS}[t_h]$ and expressed in watt-hour per BS (Wh/BS). Finally, the BS life-cycle model assesses the total environmental impacts per BS across multiple impact categories throughout its entire life cycle. These LCIA results are calculated using EF 3.1 [197], which covers 16 impact categories. They are expressed in different indicator units for the entire BS lifetime (e.g., kgCO₂eq/BS) and are gathered into the column vector I_{BS} . The latter two output results are BS-centric because they are expressed for one BS and can then be scaled by the number of BSs within the network for larger-scale studies. The calculation approaches for power consumption and life-cycle assessment results are detailed in Chapters 5 and 6, respectively. Other perspectives for these assessment results can be computed as well, such as the energy consumption per frequency band, or the production impacts per BS hardware component.

4.3.5 Practical implementation

The integrated network model aims to predict network assessment results for a given hourly data traffic volume per user. This type of model can be seen as an *inverse* model [198, 199] because its outputs reflect the explanatory variables (e.g., the per-subframe transmit power and related DL throughput per user) that lead the system to produce certain behaviors reflected by its input (i.e., the transfer of

a given DL data volume per user over one hour). Therefore, the part of the network model that calculates hourly QoS metrics and energy consumption results is referred to as the *hourly inverse network model*.

Inversion of analytical models could be used to obtain the inverse network model. However, deriving analytical models of network performances, as in [200–202], is generally impractical for complex network configurations, with multiple frequency bands and nonlinear BS behaviors induced by PSSs, under realistic radio channel models. Without tractable analytical models, directly deriving an inverse network model is infeasible. Instead, *forward* modeling [198, 199] can be used to first predict the network behavior from explanatory variables, using knowledge of mathematical models of the underlying processes. Then, inverse modeling [198, 199] can be applied to derive inverse network models numerically.

The practical implementation of the proposed hourly network model thus follows a two-stage procedure. First, the forward modeling stage generates a rich set of BS operating states under controlled short-term user activity for fixed model configurations. Second, the inverse modeling stage relates the calculated hourly QoS and energy results to the hourly data traffic volume per user to fit inverse system-level models. These models are determined once for the full range of achievable network usage, enabling quick prediction of network performances for any value of the input variable. Thus, the two-stage procedure is computationally efficient because the costly forward simulation does not need to be rerun for every prediction with a given model configuration. Additionally, this approach decouples the per-subframe nonlinear stochastic network dynamics from the hourly network assessments, resulting in more robust and reproducible models. The proposed forward-inverse approach contrasts with conventional network simulators [140–155] that typically apply forward modeling only.

Figure 4.6 outlines the numerical simulation workflow of the integrated network model developed in this thesis. At the time of writing, this model is coded in MATLAB and is planned to be released as an open-source software tool for use in future works. In the forward stage, multi-frame assessments are controlled by the *user activity ratio*, which expresses the fraction of time during which users are active on average in the network. However, this ratio only reflects temporal activity and does not directly indicate the QoS or data traffic actually delivered to users. Indeed, these aspects also depend on the radio channel quality for each user, the number of active frequency bands per BS and their respective bandwidth, the interference from neighboring cells, etc. Given the user activity ratio and the BS and UE densities, the traffic model randomly activates UEs in the network across multiple BSs and for each subframe of the simulated multi-frame time period.

Next, the per-subframe physical resource load of cells in the BS of interest is fed into the BS communication performance model along with the network state (i.e., the load of the neighboring BS cells and the number of active users in each cell).

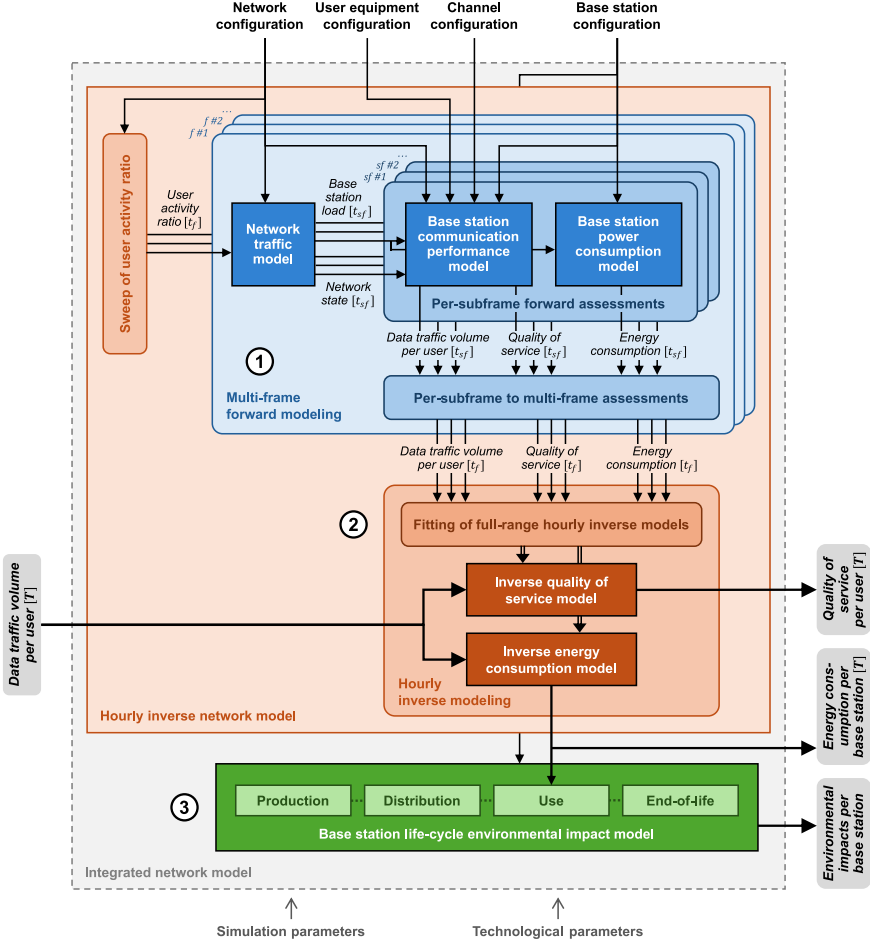


Fig. 4.6 Numerical simulation workflow of the integrated network model. For a given model configuration, the simulation of the hourly inverse network model follows a two-stage procedure: (1) the forward multi-frame assessment of quality of service and energy consumption results controlled by the user activity ratio, and (2) the inverse fitting of hourly quality of service and energy consumption models as a function of the hourly data traffic volume per user. This involves a Monte-Carlo approach to compute hourly results and a sweep of user activity ratios to cover the full achievable range of network usage. Stage (3) of the simulation assesses the base station life-cycle environmental impacts, using the energy consumption results from the hourly inverse model.

Based on these inputs and on all configuration variables, the model performs per-subframe forward assessments of the data traffic volume per user and other QoS metrics. The physical resource load of the BS of interest is also fed into the BS power consumption model. Taking into account the BS configuration, this model assesses the BS energy consumption for each simulated subframe. These per-subframe forward assessments are subsequently aggregated over the simulated period to obtain multi-frame forward assessment results.

The inverse modeling stage then uses the multi-frame forward assessments to fit hourly inverse QoS and energy consumption models. Computing the hourly results involves assessing a large number of random user activity realizations, following a Monte Carlo approach [203]. Moreover, rather than iteratively searching for the user activity ratio that achieves a single input network usage, the simulation sweeps across user activity ratios to capture the full range of achievable BS loads (from 0 to 1). This approach avoids implementing an iterative search algorithm and speeds up computation of output results with multiple input network usages. The estimated hourly QoS and energy results are then mapped as functions of the hourly data traffic volume per user. The resulting inverse relations are fitted using shape-preserving piecewise cubic interpolation [204] to produce inverse system-level models that cover the full range of network usage.

The complete integrated network model includes a third stage that assesses the environmental impacts per BS from a life-cycle perspective. The environmental impacts across all life-cycle stages depends on the BS configuration, while the use stage additionally depends on the BS energy consumption predicted by the hourly inverse network model. Moreover, the input network usage is bounded by a maximum hourly data traffic volume per user because BS load ≤ 1 . At full BS load, the network is fully saturated and unable to accommodate additional data traffic. In practice, congestion and latency degradation occur below full saturation (i.e., full BS load on average), as further discussed in Chapter 7.

4.4 Parameter estimation approach

A key objective of the proposed network model is to simulate the operation of commercial BSs under real-world conditions. This requires estimating realistic numerical values for the technological parameters of the network model (e.g., BS component efficiencies and environmental impact factors of life-cycle processes). To this end, this section introduces the approach used in Chapters 5 and 6 to estimate the technological parameters using regression analysis. Then, it describes the specific empirical data sources used for model calibration. Finally, the section explains how to quantify associated uncertainties, which is essential for conducting uncertainty and sensitivity analyses of assessment results. Although approximate, the resulting parameter values enable meaningful quantitative comparisons across different BS and RAN configurations under consistent modeling assumptions. This

contribution addresses a critical gap in the availability of up-to-date RAN-specific technological parameters in the literature.

4.4.1 Regression analysis

Regression analysis [205] is used to calibrate the parametric (possibly nonlinear) functions of the proposed network model, ensuring that the technological parameter estimates reflect empirical observations for commercial BSs. To calibrate a given parametric function, the dependent variable of the regression is set as the modeled quantity, denoted by $q(\varphi)$. The independent variables then correspond to a subset of the configuration variables, denoted by φ such that $\varphi \subseteq \{\varphi_{net}, \varphi_{BS}, \varphi_{UE}, \varphi_{chan}\}$. Denoting θ as the set of technological model parameters to be estimated, the parametric function can also be rewritten as $q(\varphi, \theta)$.

For each parametric function of the model, a dedicated dataset is constructed to estimate the associated technological parameters. Each dataset consists of D empirical observations defined by known variable configurations $\Phi = \{\phi_1, \phi_2 \dots \phi_D\}$ and corresponding target values $Y = \{y_1, y_2 \dots y_D\}$. These observations are drawn from the empirical data sources described in Section 4.4.2. Calibration then consists of finding the parameter estimates $\hat{\theta}$ that minimize the discrepancy between the target observations Y and the model predictions $q(\Phi, \theta) = \{q(\phi_1, \theta), q(\phi_2, \theta) \dots q(\phi_D, \theta)\}$. Formally, the technological parameter estimates are obtained by solving the nonlinear least squares problem

$$\hat{\theta} = \arg \min_{\theta} \left(\sum_{d=1}^D \left(y_d - q(\phi_d, \theta) \right)^2 \right). \quad (4.3)$$

In practice, this optimization problem is solved using MATLAB routines based on trust-region algorithms [206]. For each calibration, admissible ranges of technological parameters are set based on physical constraints (e.g., positive masses), and the starting point for optimization is determined based on rough prior estimates.

In Table 4.1, the domain of model variables defines the admissible ranges of variables for which the proposed network model is considered valid. Therefore, the numerical parameter estimates provided in this thesis can be used to model networks and BSs whose configurations lie within this domain. Yet, these estimates cannot be applied directly to assess other configurations. To extend the validity domain of the proposed model, its parametric functions may need to be adapted, and the set of empirical data used for calibration should be expanded.

4.4.2 Specific empirical data sources

In addition to the scientific literature, the development and calibration of parametric functions in the network model rely on four specific sources of empirical data: (i) on-site measurements, (ii) hardware teardowns, (iii) technical documenta-

tion, and (iv) practical network configuration. These data sources are then used in Chapters 5 and 6 to construct specific datasets for estimating the numerical values of associated technological parameters.

4.4.2.1 On-site measurements

On-site counters installed at each BS site monitor a broad range of metrics related to QoS and energy consumption. Typically, reported on-site measurements are statistical metrics at the hourly time scale, e.g., physical resource load (maximum and average), the total data traffic volume, number of connected users (maximum and average), power consumption (maximum and average), etc. QoS-related measurements are usually reported per cell, while energy-related measurements are reported per physical component. The strength of these measurements lies in their ability to reflect the practical operating states of BS across a realistic range of physical resource loads. Yet, there are limitations. First, on-site measurements must be provided by the owner MNOs, usually restricting data export to a limited number of BSs for practical reasons. Second, the raw and specific format of the measurements makes them time-consuming to analyze. Third, measurement data are confined to the subset of BS configurations actually deployed in the RANs.

In the network model development process, on-site measurements are used to build models for assessing QoS and power consumption. The dataset comprises around 100 hourly metrics taken over a one-week period in 2023 for two macro BS deployed in Belgium and supporting up to five frequency bands in 4G-LTE and 5G-NR. Figure 4.7 shows the measurements of four metrics for one BS that only supports 4G-LTE. On-site measurements play a central role in grounding the model in real operating conditions. Due to confidentiality agreements, the dataset of measurements cannot be disclosed.

4.4.2.2 Hardware teardowns

Hardware teardowns of specific BS components enable quantification of their material composition, as well as precise modeling of the BS architecture. This process includes mechanical disassembly, identification of subcomponents and materials, weight and size measurements, chemical decapsulation of ICs, etc. The strength of hardware teardowns is that they offer a detailed understanding of the BS architecture and enable precise quantification of its composition tailored to study requirements. However, the teardown process is time-consuming and requires physical access to the components, with approval to alter them.

In the model development process, hardware teardowns are used to conceptualize BS architecture representations and to develop the life-cycle environmental impact model. Two types of teardown data are used: internal and external. Internal teardowns were carried out specifically for this thesis, examining a BBU, a remote RU, and an AU of a macro cellular BS supporting several frequency bands including 4G-LTE at 1.8 GHz. Figure 4.8 shows pictures of these components disassem-

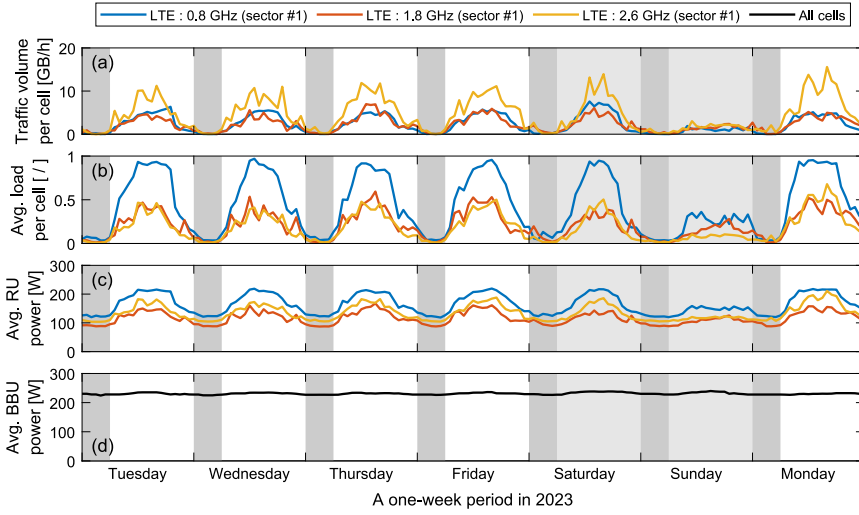


Fig. 4.7 Examples of hourly on-site measurements over a one-week period in 2023 for one macro base station supporting 4G-LTE: (a) downlink data traffic volume per cell, (b) average physical resource load per cell, (c) average power consumption per radio unit (RU), and (d) average power consumption of the baseband unit (BBU). (a)–(c) shows measurements for one sector only, while (d) shows a measurement for the nine cells of the base station. Nighttime periods are indicated in dark gray and weekend days are in light gray.

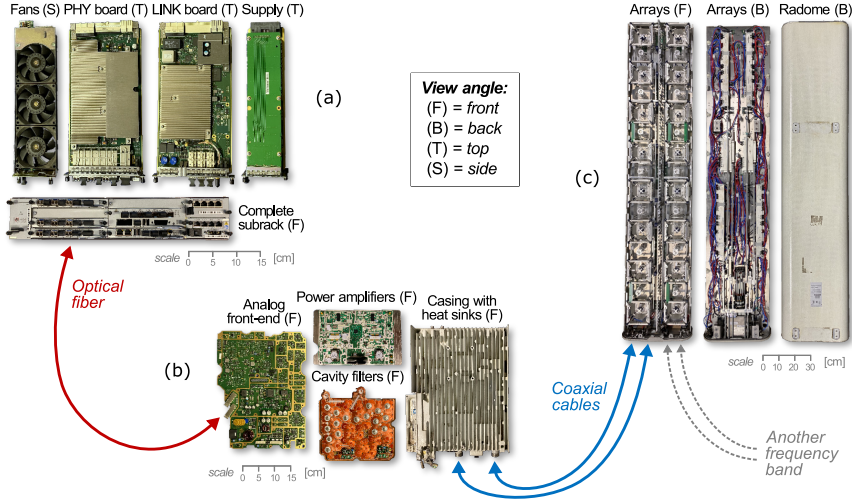


Fig. 4.8 Pictures of disassembled components of a macro base station, carried out through internal teardowns: (a) a baseband unit, (b) a remote radio unit, and (c) a passive antenna unit. The scale of these pictures is different for each component. Power cables are not shown, and no internal teardown of a power supply unit was carried out.

bled. Additionally, 15 external teardowns of BS components were obtained from various external sources, covering other BS configurations ranging from legacy 3G-UMTS RUs to an up-to-date 5G-NR AAU with massive-MIMO at 3.5 GHz, a micro RU, as well as a PSU. Altogether, these teardowns ensure that the life-cycle model accurately reflects the material composition of deployed hardware in RANs. More details about these teardowns are available in supplementary material of [JP3].

4.4.2.3 Technical documentation

Technical documentation from manufacturers provides comprehensive description and technical specification of physical BS components. In accordance with European Telecommunications Standards Institute (ETSI) Recommendation ES 202 706 [207] and EU Recommendation 2021/2279 [208], manufacturers now include both the power consumption range and the bill of materials in documentation of their products. Unlike on-site measurements and hardware teardowns, technical documentation covers the full range of commercially available BS components with various configurations. Another advantage is that it provides the power consumption of BS components at full load – a level rarely reached on an hourly basis during normal operation, but useful for modeling purposes. A limitation of these secondary data sources is that they sometimes lack the level of details needed for in-depth modeling. Additionally, reported power consumption values are limited to the four reference load levels recommended in [207] (i.e., 0, 0.3, 0.5 and 1).

In the model development process, technical documentation are used to supplement on-site measurements in the development of the BS power consumption model. The collected documentation covers more than 100 BS components, which greatly expands the available dataset for model calibration. Technical documentation also supports conceptualizing BS architecture representations. Furthermore, environmental declarations of BS components are used to complement hardware teardowns in the development of the BS life-cycle environmental impact model. Technical documentation therefore bridges the gap when measurements or teardowns are unavailable. It also provides a systematic basis for estimating the power model parameters across a wide range of configurations. Due to confidentiality agreements, technical documentation from manufacturers cannot be disclosed.

4.4.2.4 Practical network configuration

Knowledge of the practical configuration of all BSs within a RAN helps to model how the different BS components are configured in practice. This data includes, e.g., the BS locations, their respective number of sectors and bands, transmit power settings, supported protocols, etc. Additional information from MNOs provides insight into field practices surrounding RANs, particularly regarding the installation, operation and de-installation of BSs. This helps to ensure that the model remains grounded in real-world practices, even if it does not always reflect the latest state-of-the-art practices.

In the model development process, the practical network configuration of one MNO in Belgium is used to identify typical network and BS configurations. This encompasses all active BS in that specific RAN in 2023, including over 4000 sites. This dataset anchors the model to realistic deployment patterns, ensuring that simulated networks closely resemble actual deployment. Due to confidentiality agreements, the dataset of practical network configuration cannot be disclosed.

4.4.3 Uncertainty quantification method

In LCE, qualitative and/or quantitative uncertainty analysis is essential to support informed decision-making. However, this aspect is often overlooked when assessing the techno-environmental performances of products [107, 209]. To prevent this limitation, this thesis explicitly quantifies the uncertainty in assessment results arising from model calibration and technological parameter estimation.

In Chapters 5 and 6, uncertainty quantification is based on the *NUSAP scheme*, which is designed to express and communicate uncertainties in numerical results. This scheme suggests characterizing uncertain results through five complementary elements, from the most quantitative to the most qualitative [107, 209].

- (N) The **numeral** corresponds to the “typical” or “most representative” numerical value of the result (e.g., “5.96”).
- (U) The **unit** is the base for operations on the numerical result (e.g., “kg”).
- (S) The **spread** provides an indication of the result variability (e.g., “ $\pm 15\%$ ”).
- (A) The **assessment** expresses a judgment of the (un)reliability associated with the previous quantitative description of the result (e.g., “low confidence”).
- (P) The **pedigree** conveys information about the production process of the result (e.g., “experimental data”).

For instance, the spread captures uncertainty arising from temporal and spatial variability, whereas the assessment captures uncertainty from modeling assumptions and measurement errors. Additionally, the pedigree aims to provide information on model relevance and epistemological uncertainty [73, 107, 209].

Accordingly, the integrated network model first calculates the “most representative” *numeral* for each assessment result associated with a specific *unit*. Uncertainty analysis then communicates about the *spread* and *assessment* of the calculated results, in line with the heuristic definition “uncertainty = variability + error” from Heijungs [107]. In this definition, *variability* is the intrinsic part of uncertainty that cannot be reduced by the modeling approach (e.g., technological variability between years or manufacturers). Conversely, the *error* part of uncertainty stems from limited knowledge that could be reduced by an improved modeling approach (e.g., errors in the model structure, due to a lack of data, or in the use of proxies). This thesis quantitatively assesses these two parts of uncertainty arising

from the proposed modeling approach. However, it does not address external sources of uncertainty, such as uncertainty within empirical data, LCI databases, LCIA methods, etc. The *pedigree* of the results is also excluded from uncertainty quantification because this element is inherently qualitative.

In the proposed network model, uncertainty in the calibrated parametric functions is represented by lognormal distributions [73, 107, 210]. This specific probability distribution is chosen for three reasons. First, it is strictly positive definite, which ensures that modeled quantities (e.g., component masses) and subsequent network assessment results (e.g., in terms of energy consumption or environmental impacts) are physically meaningful. Second, it allows for the analysis of multiplicative order-of-magnitude uncertainty (e.g., from $\times 1/10$ to $\times 10$) rather than additive symmetrical uncertainty (e.g., from -10% to $+10\%$), which is useful for considering highly uncertain parts of the model. Third, it aligns with the observed relative residuals from regression analysis, as shown in the supplementary material of [JP3]. From Equation (4.3), the relative residual for an observation d is

$$\epsilon_d = \frac{y_d - q(\phi_d, \hat{\theta})}{q(\phi_d, \hat{\theta})}. \quad (4.4)$$

Overall, uncertainty introduces a *stochastic* dimension to the calculated results, on top of the *deterministic* network assessments.

Mathematically, the probability density function (PDF) of a random variable Y that follows a lognormal distribution is

$$f_Y(y) = \frac{1}{y\sqrt{2\pi}\sigma} \exp\left(-\frac{(\ln(y) - \mu)^2}{2\sigma^2}\right), \quad (4.5)$$

where μ and σ are the mean and standard deviation of the underlying Gaussian distribution in the log-domain. In the linear domain, the median of the lognormal distribution is $\mu^* = \exp(\mu)$, which is lower than its mean (i.e., $\exp(\mu + \sigma^2/2)$). The main advantage of this distribution is its semi-infinite support $y \in [0, \infty[$. However, this distribution is also positively skewed in the linear domain, unlike its underlying Gaussian distribution that is symmetrical in the log-domain. Due to this skewness, the median is usually preferred to the mean as the "most representative" value of a lognormally distributed variable [73, 107, 210]. Furthermore, the spread of a lognormal distribution can be characterized by its geometric standard deviation (GSD), defined as $\sigma^* = \exp(\sigma)$. In the linear domain, this reflects a *multiplicative* spread that can be used to model order-of-magnitude uncertainty, while it reflects the *additive* spread in the log-domain. Thus, the GSD is generally used to represent uncertainty with lognormally distributed variables.

In practice, the lognormal distribution that models the uncertainty in each para-

metric function of the network model is determined in four steps.

- (1) The **median** of the lognormal distribution is set as the deterministic prediction of the parametric function, denoted by $q(\varphi, \hat{\theta})$.
- (2) The **variability-related GSD**, denoted by σ_v^* , is calculated by fitting a lognormal distribution to the relative residuals from regression analysis (when sufficient data is available). For example, a GSD of 1.40 corresponds to an asymmetrical variability with inter-quartile range (IQR) ranging from -20% to $+25\%$ relative to the median.
- (3) The **error-related GSD**, denoted by σ_e^* , is estimated from a multiplicative error factor (e.g., 3) that reflects the expected range of minimum to maximum possible observations (e.g., $[1/3, 3]$). As in [210], the corresponding GSD is then the square root of this factor (e.g., $\sqrt{3} = 1.73$). The error factor is estimated from judgments about the reliability of the calibrated models and their associated variability. These judgments were made by the model developers (including myself) to communicate the anticipated magnitude of error introduced by the modeling approach in network assessment results.
- (4) The **total uncertainty** combines the variability and error parts of uncertainty under the assumption of independent lognormal distributions [210]. The resulting GSD is calculated from the GSDs of both parts as

$$\sigma_t^* = \exp \left(\sqrt{\ln(\sigma_v^*)^2 + \ln(\sigma_e^*)^2} \right). \quad (4.6)$$

Finally, the overall uncertainty in assessment results is calculated using Monte Carlo simulations [73, 107] to propagate uncertainty within the network model.

4.5 Typical base station configurations

This last methodological section defines a set of typical BS configurations derived from observed configurations in the RAN of one MNO in Belgium. These typical configurations are then used in Chapters 5 and 6 to illustrate basic applications of the proposed BS models. All typical configurations consist of single-band BSs, enabling finer result comparisons when modifying model variables other than the number of bands. Specifically, Table 4.3 defines the five typical BS configurations identified in terms of the model variables φ_{BS} . Only the variables that differ between configurations are reported in this table, while default values listed in Table 4.1 apply to all remaining model variables. More sophisticated multi-band BS configurations can subsequently be constructed by combining these typical configurations, as investigated in Part II of this thesis.

In Table 4.3, the first four configurations correspond to macrocell BSs, and the last configuration, *Mi-L18*, corresponds to a microcell BS. All macro BSs have three

Table 4.3 Typical base station configurations

Variable	<i>Ma-L08</i>	<i>Ma-L18</i>	<i>Ma-L26</i>	<i>Ma-N35</i>	<i>Mi-L18</i>
h_{BS} [m]	25	25	25	25	10
N_S [#]	3	3	3	3	1
T_{life} [years]	10	10	10	10	5
κ_{prot}	4G-LTE	4G-LTE	4G-LTE	5G-NR	4G-LTE
κ_{duplex}	FDD	FDD	FDD	TDD	FDD
f [GHz]	0.8	1.8	2.6	3.5	1.8
B [MHz]	10	20	20	100	20
N_L [#]	2	2	4	8	2
N_{TRX} [#]	2	2	4	64	2
P_{TX}^{max} [W]	40	40	20	3.125	5
P_{TX}^{full} [W]	40	40	20	3.125	5
ψ_{hHPBW} [°]	65	65	65	90	–
G_{TX}^{max} [dBi]	16	16	16	23	0
κ_{ABF}	without	without	without	with	without
δ_{cable} [/]	0	0.8	0.8	1	1
κ_{RU}	RFU	RRU	RRU	AAU	RRU
$\kappa_{PA,arch}$	Doherty	Doherty	Doherty	Class-AB	Class-AB
$\kappa_{PA,tech}$	LDMOS	LDMOS	LDMOS	GaN	GaAs

sectors with directional antennas, while the micro BS supports a single cell with an omnidirectional antenna. The lifetime of macro BSs is set at 10 years, while that of the micro BS is set at 5 years. Three traditional macro BS configurations – *Ma-L08*, *Ma-L18*, and *Ma-L26* – operate at frequencies of 0.8, 1.8, and 2.6 GHz with the 4G-LTE protocol in FDD and 10, 20, and 20 MHz bandwidths, respectively. The micro BS also uses 4G-LTE in FDD with a 20 MHz bandwidth at 1.8 GHz. All these configurations employ RRUs, except *Ma-L08* that employs RFUs. These RUs embed 2 or 4 TRXs, transmitting up to 80 W per cell for macro BSs and 10 W per cell for the micro BS. The *Ma-N35* configuration is the only one that supports the 5G-NR protocol and operates at 3.5 GHz with a 100 MHz bandwidth in TDD. It employs AAUs implementing ABF with 8 spatial data layers and 64 TRXs, and provides a total transmit power of 200 W per cell. Since the output power per PA is lower in *Ma-N35* and *Mi-L18*, their PA architecture is assumed to be Class-AB, while the other configurations implement the Doherty architecture.

The five typical BS configurations also serve as references to validate the different parts of the integrated network model. Specifically, model validation aims to demonstrate the effectiveness of the proposed models in assessing these specific BS configurations. Thus, unlike uncertainty quantification that determines model precision, model validation evaluates model accuracy [205]. In this thesis, the power consumption model is validated in Chapter 5, the life-cycle environmental impact model in Chapter 6, and the communication performance model in Appendix A.3. The validation strategy for these models relies on different validation sets contain-

ing relevant empirical observations. For validation purposes, these observations must be independent of those used to calibrate the analytical model equations via regression analysis. Therefore, the validation sets differ from the initial datasets used to estimate the technological model parameters. These validation sets are described in more detail in the following chapters.

Summary

This chapter introduces the methodology used in the thesis to develop an integrated parametric model of RANs. This model aims to assess the techno-environmental performances of mobile Internet access within a LCE framework. It focuses on commercial macrocell and microcell BSs that support one or more sub-6 GHz frequency bands in 4G-LTE and 5G-NR. The integrated RAN model combines bottom-up models of communication performance, power consumption, and life-cycle environmental impacts for BSs. These BS models depend on multiple configuration variables and are linked to a network traffic model via the physical resource load. The input variable that controls the traffic model is the hourly data traffic volume per UE. This modeling approach enables the flexible analysis of a wide range of RAN configurations and operating conditions. In practice, the RAN model is implemented through a forward-inverse simulation workflow that efficiently relates the network usage to network assessment results. The proposed approach to estimating realistic technological model parameters and quantifying the associated uncertainties relies on regression analysis of specific empirical data sources. A set of five typical BS configurations is also defined to generate illustrative results and to validate model predictions in the following chapters.

5

Parametric model for power consumption of base stations

This chapter develops a parametric model for assessing the power consumption of commercial BS architectures, specifically macro- and micro-cellular BSs that support one or more sub-6 GHz frequency bands in 4G-LTE or 5G-NR. This model builds upon the state-of-the-art power models for BSs reviewed in Chapter 3 and seeks to address the associated research gaps. Moreover, the proposed model is designed to be integrated within the parametric RAN model in order to contribute to addressing RQ1. Following the methodology introduced in Chapter 4, this chapter develops analytical power models for different BS components based on variables such as the carrier frequency, bandwidth, transmit power, etc. These models apply to both the radio-frame and hourly time scales, thereby capturing nonlinear effects induced by sleep modes and PSSs. In addition, realistic technological parameter values are estimated using specific empirical data sources. Overall, the proposed power consumption model enables quantitative assessments and consistent comparisons of various BS configurations under different operating conditions.

This chapter begins with a refined goal and scope definition for the BS power model in Section 5.1, followed by its specific modeling approach in Section 5.2. Then, Section 5.3 develops an analytical power model for PAs, and Section 5.4 extends the analytical power model to the entire BS. To ensure applicability of the model in real-world contexts, Section 5.5 derives technological parameter estimates using regression analysis of empirical data and quantifies the associated uncertainties. Next, Section 5.6 illustrates the practical use of the proposed power

consumption model by assessing five typical BS configurations across three operating modes. Finally, Section 5.7 validates the power model against independent observations, and Section 5.8 discusses the main contributions and limitations, as well as perspectives for future works. This chapter adapts and extends the BS power model introduced in [CP2]. This publication resulted from a collaboration with Youssef Agram, who contributed to the conceptualization of the analytical BS power model presented in Section 5.4 and to the analysis of the raw empirical data yielding the parameter estimates provided in Section 4.4.

5.1 Goal and scope

The specific goal and scope of the BS power consumption model complement the general goal and scope of the integrated RAN model defined in Section 4.1. Specifically, the BS power model is developed based on the ITU Recommendation L.1310 [187] for evaluating the energy efficiency of telecommunication equipment.

Within the integrated RAN model, the proposed BS power model assesses the hourly energy consumption of the entire BS during its use stage, including both DL and UL operations. However, this assessment only accounts for the electrical energy consumption at the BS site. Thus, the model excludes power losses in the electricity grid and due to primary-to-secondary energy conversion (e.g., in gas-fired power plants). Consistent with the RAN model boundaries, the BS power model includes all communication-specific components of the BS but excludes its support components, core network components, data centers and UEs. The proposed BS power model is designed to assess a wide range of BS configurations based on the set of model variables φ_{BS} defined in Section 4.3.3.

Since the QoS provided by a given BS configuration also depends on communication-related variables (e.g., the signal propagation environment, BS and UE densities, etc.), a communication performance model is needed to relate the BS energy consumption to its functional performance. Such a performance model is included in the integrated RAN model (see Section 4.3.1) but is not presented in this thesis. Combining these two BS models then allows for the derivation of other performance metrics, such as energy intensity metrics per GB of data traffic, per user, per km^2 of coverage, or per MHz of occupied spectrum (or their inverse efficiency metrics), as further discussed in Chapter 7.

5.2 Modeling approach

The modeling approach for the BS power consumption model builds on the modeling approach for the integrated RAN model described in Section 4.2. Specifically, the BS power model employs the functional representation of the BS architecture

for model development, but uses the physical representation for technological parameter estimation and model validation.

5.2.1 Modeling strategies

The BS power model only accounts for active electrical and electronic BS components because passive electrical and mechanical BS components are not directly connected to a power source. The functional architecture representation of a large-cell (macro or micro) BS consists of five types of active components: the DBB, AFE, AS, ACSs, and UPS (see Section 4.2.3). Two modeling strategies are used together to model the power consumption of these components and in the BS power model: the modular modeling strategy and the parametric modeling strategy [189].

The modular strategy [189] represents the BS as a set of reusable modules, each corresponding to a specific component. These modules are first modeled separately, and then aggregated together to constitute the entire BS. The parametric modeling strategy [189], in turn, characterizes the power consumption of each BS component through a set of component-related parameters. The resulting parametric (often nonlinear) functions depends on φ , which denotes the subset of BS configuration variables φ_{BS} that affects the power consumption model (see Section 4.3.3), such that $\varphi \subseteq \varphi_{BS}$. For instance, φ includes the bandwidth B , the carrier frequency f , the number of TRXs N_{TRX} , etc. As explained in Section 4.4, regression analysis is used during model development to determine these parametric functions and to estimate the associated technological parameters.

5.2.2 Input model variable

The power consumption of BS components fluctuates dynamically over time, as shown in [JP1] and [166, 211]. These fluctuations depend on the usage level of the BS, which is mainly determined by the number of active UEs and their data traffic. It also depends on the implemented PSSs. However, empirical data shows that the dynamic power consumption of BS components and subcomponents, particularly PAs, is primarily driven by the physical resource load rather than by the amount of transmitted data bits per PRU. This is supported by hourly on-site measurements displayed in Figure 5.1 for six RUs.

Figure 5.1(a) illustrates the relationship between the average power consumption and average physical resource load for three different RU configurations across three frequency bands and two sectors of the same BS. In this case, the relationship is clear and even linear because no PSS was implemented on this BS during the measurement period. On the other hand, Figure 5.1(b) shows a more noisy and less consistent relationship between the DL data traffic volume and the average RU power consumption. This relationship is also less linear, e.g., in sector #1 at 0.8 GHz. The weaker fit arises because the traffic volume also depends on additional factors such as radio channel quality, interference, and UE distribution,

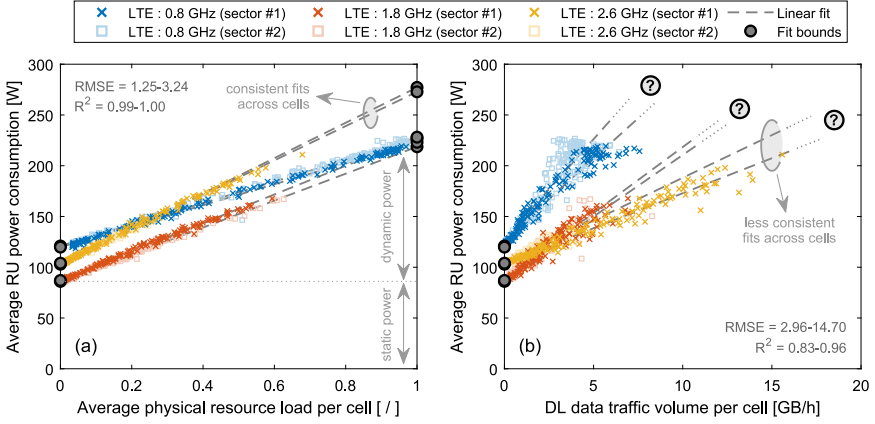


Fig. 5.1 Hourly on-site measurements of the average power consumption of six radio units (RUs) as a function of (a) average physical resource load, and (b) hourly downlink (DL) data traffic volume. The relationship with physical resource load is nearly linear, consistent across cells, and upper bounded at 1. The relationship with traffic volume is more noisy, cell-specific, and its upper bound may vary for each cell and is unknown a priori.

decoupling data traffic from physical resource load. Overall, this suggests that identical RU configurations yield consistent relationships with the load across different cells, whereas the relationships with the data traffic volume differ to a greater extent between cells, even with identical RU configurations.

The physical resource load is therefore chosen as the input variable of the proposed BS power model to represent the BS usage level. This choice offers three key advantages. First, it improves the goodness-of-fit of power models and eliminates the need to explicitly model the radio channel, traffic generation, inter-cell interference, etc. While this simplifies the modeling of BS power consumption, the complementary communication performance model is required to model the QoS. Second, it ensures that the power model for a given BS configuration can be reused regardless of the BS site. This would not be possible with traffic-based models because they require cell-specific calibration. Third, the physical resource load has fixed bounds between 0 and 1, providing a known upper limit for model extrapolation (i.e., 1). This is useful when models are derived from empirical on-site measurements that do not cover the full range of load. In contrast, the maximum DL data traffic volume varies from cell to cell and is unknown a priori.

Although the BS power model accounts for energy consumption from both DL and UL operations, the physical resource load is calculated only for the DL (see Section 4.2.2). However, most of the dynamic BS power consumption comes from the PAs, as these components are highly load-dependent. Since PAs are only active in the DL, it is appropriate to use the physical resource load to model the BS power

consumption. Moreover, previous studies have shown that energy consumption from DL operations dominates the total energy consumption in large-cell BSs [166, 169, 170], which motivates finer modeling of this direction. In addition, about 90% of mobile data traffic occurs in the DL, and the average resource load is typically $\times 2$ -5 in the DL than in the UL (see Appendix A.2). This suggests that the DL is the binding direction governing the BS operating state and driving the PSSs.

5.2.3 Model structure

Inspired from [168], the structure of the BS power model combines the modular and parametric modeling strategies to compute the total BS power consumption, denoted by P_{BS} . Since a BS may serve multiple sectors and support multiple frequency bands, four types of functional BS components are defined for each cell¹: the DBB, the AFE, the AS, and the ACS. The power consumption of these components for a cell c are respectively denoted by $P_{DBB,c}$, $P_{AFE,c}$, $P_{AS,c}$ and $P_{ACS,c}$. These values can differ for the N_C cells of the BS depending on their configuration (represented by φ) and operating conditions (i.e., the load x). A fifth component is the UPS, which serves the entire BS and whose power consumption is denoted by P_{UPS} . The total BS power consumption is then calculated as

$$P_{BS} = \sum_{c=1}^{N_C} \left(P_{DBB,c} + P_{AFE,c} + P_{AS,c} + P_{ACS,c} \right) + P_{UPS}, \quad (5.1)$$

where each term is a function of φ and x such that, e.g., $P_{BS} = P_{BS}(\varphi; x)$.

The energy consumption of PAs that comprise the AS is known to dominate the energy consumption of macro BSs and, to a lesser extent, micro BSs [131, 169, 170, 212]. The power consumption of PAs is also highly load-dependent and typically nonlinear with respect to its instantaneous output power [131, 169, 170, 172]. However, the PA modeling is generally overlooked in existing BS power models [131, 169, 170, 212]. For this reason, the proposed BS power model first focuses on modeling PAs in Section 5.3, before modeling the entire BS in Section 5.4.

5.2.4 Average power consumption

In the integrated RAN model, the BS power model calculates the BS energy consumption on an hourly basis. However, the power consumption of BS component varies over shorter time scales (typically at the multi-frame, subframe, or symbol level) because resource allocation and other communication protocol operations occur at these time scales (see Section 4.2.2). Since the integrated RAN model runs forward simulations at the multi-frame time scale (see Section 4.3.5), the hourly average BS power consumption, denoted by $\bar{P}_{BS}[t_h]$, is obtained by averaging N_f sam-

¹In this thesis, a *cell* is defined as one frequency band in one sector of one BS.

ples of multi-frame BS power consumption assessments. This yields

$$\bar{P}_{BS}[t_h] = \frac{1}{N_f} \sum_{j=1}^{N_f} P_{BS}[t_f^{(j)}], \quad (5.2)$$

where $P_{BS}[t_f^{(j)}]$ is the BS power consumption of the j th simulated multi-frame in hour t_h . Then, the hourly BS energy consumption is calculated from $\bar{P}_{BS}[t_h]$ as

$$E_{BS}[t_h] = \bar{P}_{BS}[t_h] T_h \quad (5.3)$$

which is expressed in watt-hours as $\bar{P}_{BS}[t_h]$ is expressed in watts and $T_h = 1$ hour.

5.3 Power amplifier power model

Within the BS power model, the PA power model aims to calculate the per-symbol PA power consumption for different per-symbol output power. In the integrated RAN model, the per-symbol PA output power is assumed to correspond to the per-symbol transmit power per PA. This section first provides an overview of PAs for wireless communications. Then, it proposes a statistical model of the transmit signal at the per-symbol time scale, given that the envelope of an OFDM symbol fluctuates at the instantaneous time scale. Next, it develops per-symbol PA power models that apply to OFDM signals for five common PA architectures. Based on these models, a generalized PA power model is proposed for approximating all PA architectures, enabling their comparison and flexible integration in the BS power model. Finally, the section explains how to account for realistic PA efficiencies achievable with different semiconductor technologies.

5.3.1 Power amplifier overview

In BSs, the PA is a subcomponent responsible for amplifying low-power RF signals up to the desired transmit power. Several PAs compose the AS of a BS, which operates exclusively in TX for the DL. The PA is a critical subcomponent in the BS power model, as it typically accounts for a large share of the total BS power consumption and is highly dependent on the physical resource load [131, 169, 170, 172, 212]. In the proposed BS power model, the PA is modeled as illustrated in Figure 5.2(a) with two inputs: the RF signal input power p_{in} and the PA supply power p_{supply} , and one output: the RF signal output power p_{out} .

The ideal and actual output power responses as a function of input power are depicted in Figure 5.2(b). Since the PA supply power is limited, the output power is also limited by a maximum output power. Consequently, the PA exhibits two operating regions: a *linear* region and a *saturation* region [213]. These regions are separated by the so-called *1-dB gain compression point* ($P1dB$), which is the point at

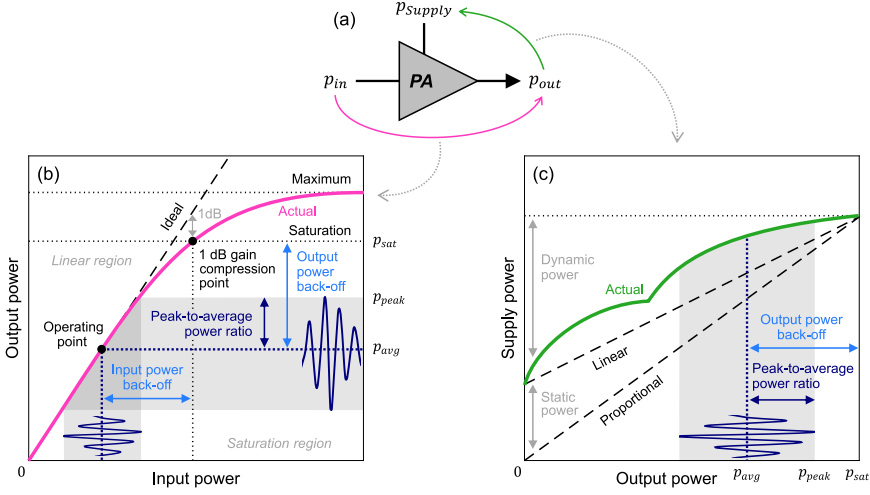


Fig. 5.2 Overview of the power amplifier (PA) model: (a) conceptual three-port subcomponent with two inputs and one output, (b) ideal and actual output power responses as a function of input power, and (c) proportional, linear and actual supply power responses as a function of output power (adapted from [213, 214])

which the actual output power is 1 dB lower than the ideal output power due to the nonlinearity in the PA [213]. The corresponding output power is referred to as the saturation output power, denoted by p_{sat} . Maintaining output signal linearity with respect to the input signal is essential in wireless communications systems, particularly in mobile networks [213, 215, 216]. Therefore, the PA typically operates at an average input power set below the P1dB, with an input margin referred to as the *input power back-off* (IPBO). In the output power domain, the *output power back-off* (OPBO) corresponds to the ratio between p_{sat} and the average output power, denoted by p_{avg} . To avoid excessive distortion, the OPBO must be set to keep the peak output power of the RF signal, denoted by p_{peak} , lower than the saturation output power, i.e., $p_{peak} \leq p_{sat}$.

The second important aspect of the PA model is the relationship between the output power and the PA supply power. Typically, this relationship for *continuous waveforms* (CWs) is modeled by a static power plus a dynamic power that varies nonlinearly with the output power, as illustrated in Figure 5.2(c). Thus, the PA power efficiency is maximum near P1dB, and decreases at lower output powers [213, 215]. Conversely, constant power efficiency would be obtained with a strictly proportional PA power model. The large *peak-to-average power ratio* (PAPR) of modulated RF signals with non-constant envelopes – as in 4G-LTE and 5G-NR using OFDM – is a major drawback because it forces the PA to operate well below the P1dB, thereby reducing its actual efficiency [213, 215].

5.3.2 Statistical model of the output signal

Using OFDM, the input and output signals of the PA are non-CW signals whose amplitude and power can be modeled statistically.

Input signal The OFDM signal envelope at the input of the PA can be expressed as a time-varying amplitude $a_{in}(t)$. This envelope is usually modeled as a Rayleigh-distributed random variable [213, 217–220] with PDF

$$f_A(a_{in}) = \frac{a_{in}}{\sigma^2} \exp\left(-\frac{(a_{in})^2}{2\sigma^2}\right), \quad (5.4)$$

where σ is the scale parameter. The PDF of $a_{in}(t)$ represents the fraction of time the signal envelope remains at a given amplitude. The support of the Rayleigh distribution is semi-infinite with $a_{in} \in [0, \infty[$. Accordingly, the input power $p_{in}(t) \propto (a_{in}(t))^2$ follows an exponential distribution with PDF

$$f_P(p_{in}) = \frac{1}{2\sigma^2} \exp\left(-\frac{p_{in}}{2\sigma^2}\right), \quad (5.5)$$

with mean

$$\mu_{in} = 2\sigma^2, \quad (5.6)$$

and with the semi-infinite support $p_{in} \in [0, \infty[$. This implies that the theoretical peak input power is infinite. In practice, the typical PAPR of an OFDM signal without any reduction technique ranges from 10 dB to 16 dB [213, 215, 217–219].

Output signal Since the PA output power is limited to a maximum value (see Figure 5.2), the semi-infinite Rayleigh and exponential distributions are not realistic for modeling the PA output signal. Moreover, PAPR reduction techniques (e.g., clipping) are usually implemented to restrain the signal amplitude below a specified threshold [213, 215, 217–219]. Accordingly, the proposed PA model represents the output signal amplitude $a_{out}(t)$ with a scaled Beta distribution whose support is bounded by the peak amplitude a_{peak} as $a_{out} \in [0, a_{peak}]$. The resulting PDF is

$$f_A(a_{out}) = \frac{1}{a_{peak} B(\alpha, \beta)} \left(\frac{a_{out}}{a_{peak}}\right)^{\alpha-1} \left(1 - \frac{a_{out}}{a_{peak}}\right)^{\beta-1}, \quad (5.7)$$

where α and β are the shape parameters, and the Beta function is

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)}, \quad (5.8)$$

where $\Gamma(\cdot)$ denotes the Gamma function. The corresponding PDF of the output power $p_{out}(t) \propto (a_{out}(t))^2$ is

$$f_P(p_{out}) = \frac{1}{2p_{peak}B(\alpha, \beta)} \left(\frac{p_{out}}{p_{peak}} \right)^{\frac{\alpha}{2}-1} \left(1 - \sqrt{\frac{p_{out}}{p_{peak}}} \right)^{\beta-1} \quad (5.9)$$

with mean

$$\mu_{out} = p_{peak} \frac{\Gamma(\alpha + \beta)\Gamma(\alpha + 2)}{\Gamma(\alpha)\Gamma(\alpha + \beta + 2)} \quad (5.10)$$

and bounded support $p_{out} \in [0, p_{peak}]$.

The shape of the Beta distribution depends on α and β . To obtain a unimodal amplitude distribution that approximates a bounded Rayleigh-like distribution, it is necessary to have $\alpha > 1$ and $\beta > 1$. Moreover, $\alpha = 2$ is selected to obtain a slope at the origin similar to the Rayleigh distribution. Then, the PDF of $a_{out}(t)$ given by Equation (5.7) becomes

$$f_A(a_{out}) = (\beta^2 + \beta) \frac{a_{out}}{(a_{peak})^2} \left(1 - \frac{a_{out}}{a_{peak}} \right)^{\beta-1}, \quad (5.11)$$

and the PDF of $p_{out}(t)$ given by Equation (5.8) becomes

$$f_P(p_{out}) = \frac{\beta^2 + \beta}{2p_{peak}} \left(1 - \sqrt{\frac{p_{out}}{p_{peak}}} \right)^{\beta-1} \quad (5.12)$$

with mean

$$\mu_{out} = \frac{6p_{peak}}{(\beta + 2)(\beta + 3)}. \quad (5.13)$$

Link to the peak-to-average power ratio Since the peak output power is p_{peak} and the average output power is p_{avg} , the linear scale PAPR of the output signal is

$$\nu = \frac{p_{peak}}{p_{avg}}. \quad (5.14)$$

As $p_{avg} = \mu_{out}$, combining Equations (5.13) and (5.14) yields

$$\nu = \frac{(\beta + 2)(\beta + 3)}{6}. \quad (5.15)$$

Then, β can be expressed as a function of $\nu \geq 1$ as

$$\beta(\nu) = \frac{\sqrt{24\nu + 1} - 5}{2}. \quad (5.16)$$

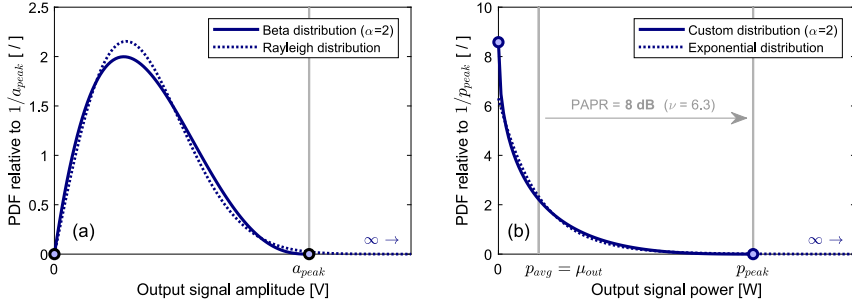


Fig. 5.3 Support-bounded probability density functions (PDFs) for (a) the amplitude, and (b) the power of an output signal with a typical peak-to-average power ratio (PAPR) of 8 dB, compared to the corresponding distributions with semi-infinite support.

This approach enables modeling the statistical per-symbol amplitude and power of the PA output signal for any PAPR value, ensuring bounded support consistent with practical PA operation. Figure 5.3 illustrates the amplitude and power PDFs for an output signal with a typical PAPR of 8 dB (i.e., $\nu = 6.3$), yielding $\beta = 3.7$.

5.3.3 Power model for different architectures

The statistical model of p_{out} is used to develop per-symbol power models for common PA architectures in wireless communications. Based on Equation (5.12), the PDF of output power for a non-CW signal with $p_{peak} = \nu p_{avg}$ is $f_P(p_{out}; p_{avg}, \nu)$. Given a CW-based power model $P_{PA}^{CW}(p_{out})$, the per-symbol PA power consumption for a non-CW signal with an average output power p_{avg} is calculated as in [215] by

$$P_{PA}(p_{avg}) = \int_0^{p_{peak}} P_{PA}^{CW}(p_{out}) f_P(p_{out}; p_{avg}, \nu) dp_{out}. \quad (5.17)$$

The maximum allowed average output power, denoted by p_{max} , is then defined as the PA output power when $OPBO = PAPR$, such that $p_{avg} \leq p_{max} = \frac{p_{sat}}{\nu}$. Thus, $p_{peak} = p_{sat}$ when $p_{avg} = p_{max}$, whereas $p_{peak} < p_{sat}$ and $OPBO > PAPR$ when $p_{avg} < p_{max}$. The rest of this section examines five PA architectures for wireless communications: (i) linear, (ii) Class-AB, (iii) Doherty (2-way), (iv) multilevel envelope tracking (ET), and (v) multilevel average power tracking (APT). Non-CW power models are developed analytically for the first three architectures, while the last two are analyzed based on numerical simulations only.

Linear A basic CW-based power model for the PA is a linear model as

$$P_{PA}^{CW}(p_{out}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{p_{out}}{\eta_{sat}}, \quad (5.18)$$

where $\eta_{sat} \in [0, 1]$ is the drain efficiency at saturation (i.e., $\eta_{sat} = p_{sat} / P_{PA}^{CW}(p_{sat})$), and $\xi \in [0, 1]$ is the normalized static power (i.e., $\xi = P_{PA}^{CW}(0) / P_{PA}^{CW}(p_{sat})$). This linear PA model corresponds to an ideal ET architecture [202, 214, 221]. Using Equation (5.17), the non-CW PA power model is also linear as

$$P_{PA}(p_{avg}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{p_{avg}}{\eta_{sat}}. \quad (5.19)$$

When $p_{avg} = p_{max}$, the maximum PA efficiency for non-CW signals is

$$\eta_{max} = \eta_{sat} \cdot (1 + \xi \cdot (\nu - 1))^{-1}. \quad (5.20)$$

This shows that $\eta_{max} = \eta_{sat}$ when the PA power model is strictly proportional, i.e., with $\xi = 0$. Otherwise, η_{max} decreases relative to η_{sat} as PAPR increases.

Class-AB The conventional Class-AB architecture operates with a bias point chosen between Class-A and Class-B operations, providing a trade-off between signal linearity and power efficiency [213, 215]. Accordingly, the CW-based power model of a Class-AB architecture is usually nonlinear [202, 214, 221] as

$$P_{PA}^{CW}(p_{out}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{\sqrt{p_{sat} p_{out}}}{\eta_{sat}}, \quad (5.21)$$

where the dynamic power consumption scales with the square root of p_{out} . At p_{sat} , the drain efficiency is still η_{sat} . Using Equation (5.17), the corresponding non-CW PA power model also scales as a square root of p_{avg} as

$$P_{PA}(p_{avg}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{2\sqrt{\nu}}{\beta(\nu) + 2} \frac{\sqrt{p_{sat} p_{avg}}}{\eta_{sat}}, \quad (5.22)$$

Then, the maximum PA efficiency for non-CW signals is

$$\eta_{max} = \frac{\eta_{sat}}{\nu} \cdot \left(\xi + (1 - \xi) \frac{2}{\beta(\nu) + 2} \right)^{-1}. \quad (5.23)$$

The PA power models for Class-AB can also be used to model either a Class-A architecture with $\xi = 1$, or a Class-B architecture with $\xi = 0$.

Doherty (2-way) The Doherty architecture is a classical PA architecture for wireless communications, offering improved efficiency for non-CW signals. The 2-way design combines a main Class-AB amplifier for most of the output signal with an auxiliary Class-C amplifier for the peak signal power [213, 215]. In [202, 214, 216],

the CW-based power model for the 2-way Doherty architecture is

$$P_{PA}^{CW}(p_{out}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{\sqrt{p_{sat} p_{out}}}{2\eta_{sat}} \cdot \begin{cases} 1 & \text{if } p_{out} \leq \frac{p_{sat}}{4} \\ 3 - \sqrt{\frac{p_{sat}}{p_{out}}} & \text{if } p_{out} > \frac{p_{sat}}{4} \end{cases} \quad (5.24)$$

At low power levels, the Doherty architecture behaves like a Class-AB architecture, but with only half the dynamic power. Using Equation (5.17), the corresponding non-CW PA power model is

$$P_{PA}(p_{avg}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{\sqrt{v}}{\beta(v) + 2} \frac{\sqrt{p_{sat} p_{avg}}}{\eta_{sat}} \cdot \begin{cases} 1 & \text{if } p_{avg} \leq \frac{p_{max}}{4} \\ \Omega & \text{if } p_{avg} > \frac{p_{max}}{4} \end{cases}, \quad (5.25)$$

where

$$\Omega = \left(1 - \frac{1}{2} \sqrt{\frac{p_{max}}{p_{avg}}}\right)^{\beta(v)} \left(2 + \frac{\beta(v) - 2}{2} \sqrt{\frac{p_{max}}{p_{avg}}} - \frac{\beta(v)}{4} \frac{p_{max}}{p_{avg}}\right) + 1 \quad (5.26)$$

Then, the maximum PA efficiency for non-CW signals is

$$\eta_{max} = \frac{\eta_{sat}}{v} \cdot \left(\xi + (1 - \xi) \frac{1}{\beta(v) + 2} \left(\left(\frac{1}{2} \right)^{\beta(v)} \left(\frac{\beta(v) + 4}{4} \right) + 1 \right) \right)^{-1}. \quad (5.27)$$

Multilevel envelope tracking In practice, the ET architecture can be implemented using amplifiers with an adjustable supply voltage [216, 222–224]. By adjusting the supply voltage, the PA saturation power can be controlled to follow the instantaneous signal power. This enables the PA to operate continuously close to P1dB, achieving higher efficiency. Assuming the dynamic power of an ET amplifier scales according to the adjusted saturation power p_{adj} as in Equation (5.21) and its static power remains constant regardless of the supply level, the CW-based power model becomes

$$P_{PA}^{CW}(p_{out}) = \xi \frac{p_{sat}}{\eta_{sat}} + (1 - \xi) \frac{\sqrt{p_{adj} p_{out}}}{\eta_{sat}}. \quad (5.28)$$

A practical implementation of this architecture generally uses a discrete number of supply levels, resulting in a multilevel ET amplifier.

Multilevel average power tracking Tracking the instantaneous signal envelope can be difficult to implement. Thus, a simplified version of ET is the APT architecture [224–226]. Instead of adapting the PA supply over a very short time interval, the APT architecture adapts the supply over a longer interval, usually one or more OFDM symbols. This strategy simplifies the practical PA implementation at the

cost of some efficiency. Similar to the multilevel ET architecture, a discrete number of supply levels is used to implement multilevel APT amplifiers.

The CW-based and non-CW power models for the five PA architectures are shown in Figure 5.4 as functions of p_{out} and p_{avg} , respectively. Figure 5.5 shows the corresponding drain efficiencies. In Figure 5.5(a), drain efficiency is calculated as

$$\eta_{PA}^{CW}(p_{out}) = \frac{p_{out}}{P_{PA}^{CW}(p_{out})}, \quad (5.29)$$

and in Figure 5.5(b) as

$$\eta_{PA}(p_{avg}) = \frac{p_{avg}}{P_{PA}(p_{avg})}. \quad (5.30)$$

Numerical values are obtained for a typical PA configuration of macrocell BSs with a saturation power of $p_{sat} = 250$ W, and a PAPR of $\nu = 8$ dB, resulting in a maximum allowed average output power of $p_{max} \approx 40$ W. For illustrative purposes, the normalized static power is set at $\xi = 0.05$, and the drain efficiency at saturation is set to $\eta_{sat} = 0.78$ for all architectures. This efficiency corresponds to the theoretical maximum efficiency of a Class-B PA [213, 215], although it may not be realistic for all architectures. Eight supply levels are considered for multilevel architectures.

For non-CW signals, Figure 5.4(b) shows that linear and multilevel ET architectures are more proportional to p_{out} and consume less power than other architectures. In Figure 5.5(b), this results in superior drain efficiency across the entire output power range, though the saturation efficiency and static power ratio are the same. Compared to the Class-AB architecture, the APT architecture linearizes PA power consumption, but does not improve efficiency at p_{max} . The Doherty architecture appears to be an interesting compromise between power efficiency and implementation complexity. It maintains efficiency close to that of the realistic multilevel ET architecture, without sacrificing too much efficiency at low p_{out} compared to the APT architecture. With a typical 8 dB PAPR, the drain efficiencies achieved at p_{max} are lower than η_{sat} : respectively 0.62 and 0.54 for linear and multilevel ET, 0.51 for Doherty, and 0.32 for APT and Class-AB architectures. With non-CW signals, the static power consumption of all PA architectures becomes non-negligible despite the low normalized static power $\xi = 0.05$ in CW-based models.

Furthermore, Figure 5.6 examines the variation of the maximum drain efficiency η_{max} with respect to the PAPR of non-CW signals in linear, Class-AB, and Doherty architectures. When $\xi = 0$, $\eta_{max} = \eta_{sat}$ for any PAPR with the linear architecture. However, it decreases by approximately 3% and 5% per dB with the Doherty and Class-AB architectures, respectively. With a static power (i.e., $\xi > 0$), a loss in η_{max} appears in the linear architecture, and the existing loss increases in other architectures. This demonstrates that using modulations with non-CW signals and high PAPR (e.g., OFDM), as well as moderate PA static power, greatly reduces the maximum power efficiency of PAs.

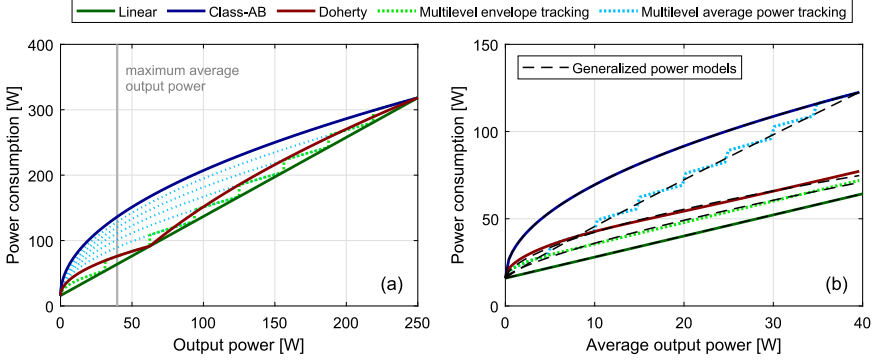


Fig. 5.4 Power consumption model for five power amplifier architectures ($\eta_{sat} = 0.78$, $\xi = 0.05$, $p_{sat} = 250$ W) with: (a) continuous waveform signals, and (b) non-continuous waveform signals ($\nu = 8$ dB, s.t. $p_{max} \approx 40$ W). (b) also shows generalized power models.

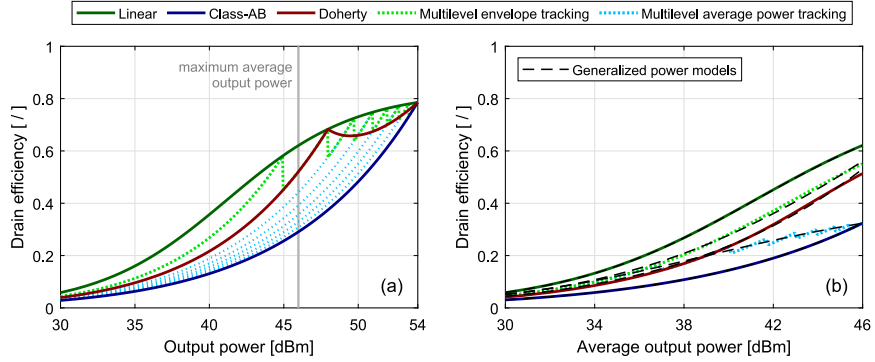


Fig. 5.5 Drain efficiency for the five power amplifier architectures ($\eta_{sat} = 0.78$, $\xi = 0.05$, $p_{sat} = 250$ W) with: (a) continuous waveform signals, and (b) non-continuous waveform signals ($\nu = 8$ dB, s.t. $p_{max} \approx 40$ W). (b) also shows generalized power models.

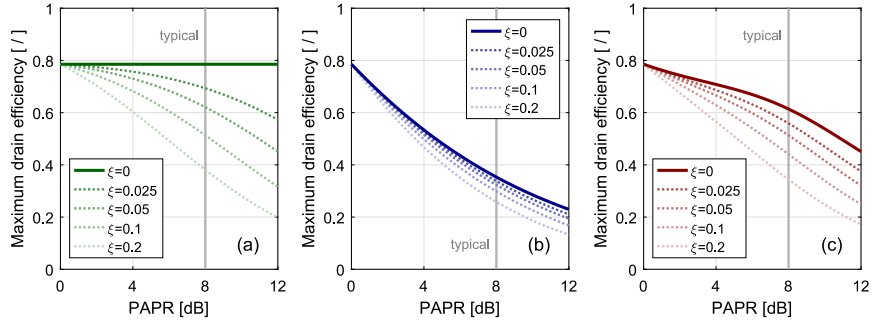


Fig. 5.6 Drain efficiency at maximum average output power vs. signal peak-to-average power ratio (PAPR) in: (a) linear, (b) Class-AB, and (c) Doherty architectures ($\eta_{sat} = 0.78$).

Table 5.1 Parameter values of the generalized power model for five power amplifier architectures ($\eta_{sat}=0.78$, $\xi=0.05$, $p_{sat}=250$ W, $\nu=8$ dB, and $p_{max}=p_{full}\approx 40$ W)

Architecture	η_{max}	ξ_{PA}	n	Error
Linear	0.62	0.25	1	no
Class-AB	0.32	0.13	0.50	no
Doherty	0.53	0.21	0.58	small
Multilevel envelope tracking	0.56	0.23	0.74	small
Multilevel average power tracking	0.32	0.13	0.93	small

5.3.4 Generalized power model

Building on the previously developed architecture-specific PA models, this thesis proposes a generalized PA power model, enabling their comparison and flexible integration in the BS power model. This model assumes that the per-symbol power consumption of a PA is the sum of a static part proportional to p_{max} and a dynamic part scaling nonlinearly with the average output power p_{avg} as

$$P_{PA}(p_{avg}) = \xi_{PA} \frac{p_{max}}{\eta_{max}} + (1 - \xi_{PA}) \frac{(p_{full})^{1-n} (p_{avg})^n}{\eta_{max}}, \quad (5.31)$$

where $\eta_{max} \in [0, 1]$ is the drain efficiency at p_{max} , $\xi_{PA} \in [0, 1]$ is the normalized static power relative to $P_{PA}(p_{max})$ (i.e., $\xi_{PA} = P_{PA}(0)/P_{PA}(p_{max})$), $n \in [0, 1]$ is the scaling exponent for the dynamic power, and $p_{full} \in [0, p_{max}]$ is the configured full-load output power. With $n = 1$, the dynamic power scales linearly with p_{avg} , whereas with $n = 0$, it results in a constant P_{PA} . Typically, η_{max} is close to η_{sat} for highly linear PA architectures with $n \rightarrow 1$. The parameter ξ_{PA} reflects ξ but relative to the non-CW PA power consumption at p_{max} . Therefore, ξ_{PA} is higher for higher η_{max} , as more efficient PA implies lower PA power consumption at p_{max} . If $\xi_{PA} = 1$, the exponent n does not affect the model and P_{PA} is constant. With an adaptive supply, p_{full} can also be set lower than p_{max} , offering PA configuration flexibility. Thus, the actual drain efficiency at full load is generally lower than η_{max} , except if $p_{full} = p_{max}$, in which case it equals η_{max} .

For the five PA configurations depicted in Figure 5.4(b) and Figure 5.5(b), Table 5.1 provides parameter values suited to Equation (5.31). It shows that linear and multilevel ET architectures have the highest drain efficiencies at p_{max} , but also the highest normalized static power. In contrast, Class-AB and multilevel APT architectures have lower drain efficiencies at p_{max} and consequently lower normalized static power. Compared to Class-AB, the multilevel APT architecture linearizes the dynamic power consumption. The generalized PA power model is exact for linear and Class-AB architectures, and results in a small approximation error for Doherty, multilevel ET, and multilevel APT architectures. Figure 5.4(b) and Figure 5.5(b)

show this close-to-exact match between the proposed generalized PA models and the architecture-specific models.

In the BS power model, the generalized PA power model is used to model the per-symbol PA power consumption. In this case, the average PA output power corresponds to the per-symbol transmit power per PA, i.e., $p_{avg} = P_{TX}[t_s]$, and the PA architecture is set by the BS configuration variables $\kappa_{PA,arch}$ (see Section 4.3.3). Additionally, the maximum and full-load average PA output power are respectively set by P_{TX}^{max} and P_{TX}^{full} , such that $p_{max} = P_{TX}^{max}$ and $p_{full} = P_{TX}^{full}$.

5.3.5 Semiconductor technologies

A final aspect influencing the PA power model is the underlying semiconductor technology, e.g., laterally-diffused metal-oxide semiconductor (LDMOS), gallium arsenide (GaAs), and gallium nitride (GaN). The achievable drain efficiency at saturation for these technologies depends on the power and carrier frequency of the transmit signal. LDMOS is generally better for high output power (i.e., 10-1000 W) and low frequencies (0-1 GHz), while GaAs is preferred for lower power and higher carrier frequencies. GaN is suited for higher frequencies than LDMOS and higher output powers than GaAs [172, 215, 216, 224].

In the PA power model, this aspect is captured by a model mapping the drain efficiency at saturation η_{sat} to the output power p_{sat} and the carrier frequency f as

$$\eta_{sat} = \frac{\eta_{tech}}{1 + a \cdot \left(\frac{p_{sat}}{P^*}\right) \left(\frac{f}{f^*}\right)^2 + b \cdot \left(\frac{P^*}{p_{sat}}\right)}, \quad (5.32)$$

where η_{tech} is the highest achievable efficiency for a given PA technology, and a and b are dimensionless technology-specific parameters representing frequency-dependent losses and low-power losses, respectively. This model is intended to inform PA design choices at the BS level. For a fixed p_{sat} , the model states that η_{sat} deteriorates as f increases, due to parasitic capacitances and the associated dynamic losses [172, 215, 227, 228]. For a fixed f , the model states that η_{sat} first increases, peaks, and then decreases as p_{sat} increases, due to parallel and series conduction losses [172, 215, 227, 228]. Moreover, the factor proportional to $p_{sat}f^2$ is motivated by the “Johnson limit” which states “ $Pf^2 = \text{constant}$ ” [215]. At this stage, it is important to note that the proposed model is mostly empirical rather than physical. Thus, a more accurate technology-aware model of PA power consumption should be developed in future works.

Figure 5.7 shows tentative η_{sat} trends with respect to f and p_{sat} for LDMOS, GaAs, and GaN technologies based on a survey compiling published PA designs [229]. Overall, this suggests that LDMOS is the best option for $p_{sat} > 10$ W and $p_{sat}f^2 < 20$ W·GHz². Otherwise, GaAs is preferable for low p_{sat} , and GaN at higher f . These trends can be incorporated into the generalized PA power model given in Equation (5.31) by estimating η_{max} based on η_{sat} via Equation (5.20) for

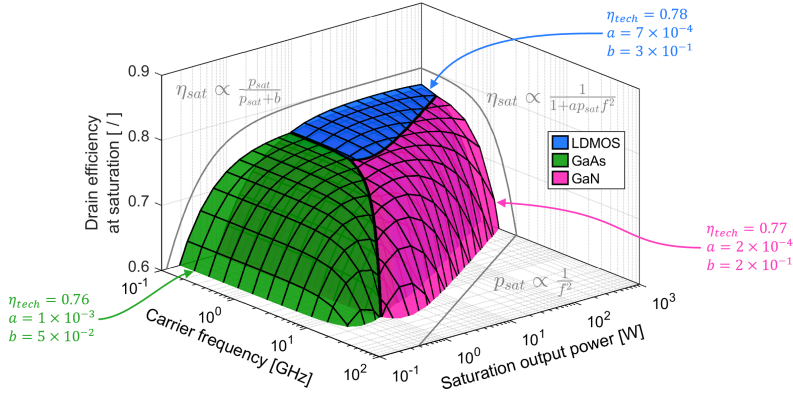


Fig. 5.7 Tentative trends of drain efficiency at saturation with respect to carrier frequency and saturation output power for laterally-diffused metal-oxide semiconductor (LDMOS), gallium arsenide (GaAs), and gallium nitride (GaN) semiconductor technologies.

linear and multilevel ET architectures, Equation (5.23) for Class-AB and multilevel APT architectures, and Equation (5.27) for the Doherty architecture. Yet, these trends are preliminary results that require further refinement.

5.4 Base station power model

The BS power model consists of parametric power models for all BS components, which comprise multiple subcomponents. This section first introduces a generic multi-state power model for BS subcomponents, which is intended to represent their power consumption across multiple operating modes. Then, for each BS component, the section models power consumption of each subcomponent operating mode and derives the corresponding multi-frame power consumption. To model a complete BS, the DBB, AFE, AS and ACSs must be individually modeled for each cell. Finally, the section determines the hourly average power model of the BS without and with PSSs. In this section, all powers are expressed in watts.

5.4.1 Generic multi-state model

Each BS component comprises multiple subcomponents dedicated to specific functions within the communication chain (see Section 4.2.3). The power consumption of each subcomponent depends on its configuration and operating conditions, both of which may vary over time. Specifically, the operating conditions depend on the physical resource load of the associated cell(s) and on the communication protocol that determines when DL and UL occur, when reference signals are transmitted,

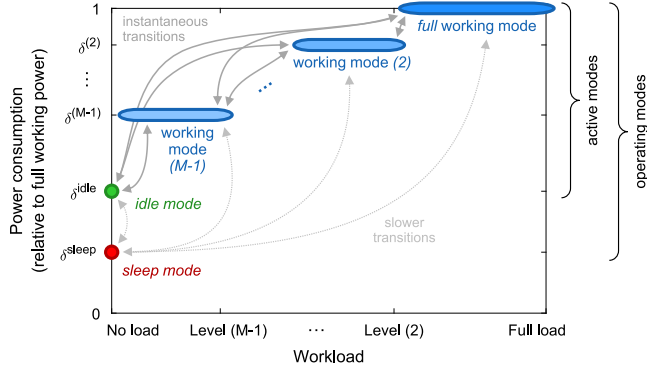


Fig. 5.8 Conceptual multi-state subcomponent model showing its operating modes in relation to power consumption and workload. The M active modes range from full working mode to working mode $(M-1)$, plus an idle mode that consumes less power at no load. Sleep mode consumes minimal power, but transitions to and from this mode are slower.

etc. As in [44, 170, 175], the proposed BS power model is built around a generic multi-state model. In this model, a limited number of states, referred to as *operating modes*, are identified for each subcomponent of the BS. This discrete modeling approach simplifies the development of the complete BS power model.

In the generic multi-state power model, a subcomponent can switch between M active modes and a single *sleep mode*. Active modes are either *working modes* or an *idle mode*. Working modes are the active modes during which the subcomponent performs useful DL or UL operations. The corresponding power consumption generally depends on the workload (e.g., physical resource load) [170, 172]. The *full working mode* occurs when the subcomponent operates at maximum power consumption, usually due to a full workload [44, 170, 175]. Conversely, the *idle mode* is an active mode designed to save energy when the subcomponent does not perform any useful operations and waits for the next task [44, 170, 175]. The single non-active mode of the multi-state model is the *sleep mode* that fully deactivates the subcomponent to save more energy than the idle mode. Figure 5.8 shows a conceptual illustration of these operating modes in relation to their power consumption and workload. Then, Figure 5.9 applies the multi-state power model to an illustrative cell configuration under a given physical resource load. Figure 5.9(a) shows the partly loaded resource grid and Figure 5.9(b) shows the corresponding operating modes for all BS subcomponents.

Full working mode The full working power consumption of most subcomponents is modeled as in [169, 170, 173] by scaling a reference power with respect to a reference situation using scaling variables. Formally, the full working power consumption $P_k^{full}(\varphi)$ of subcomponent k in a configuration described by φ is obtained

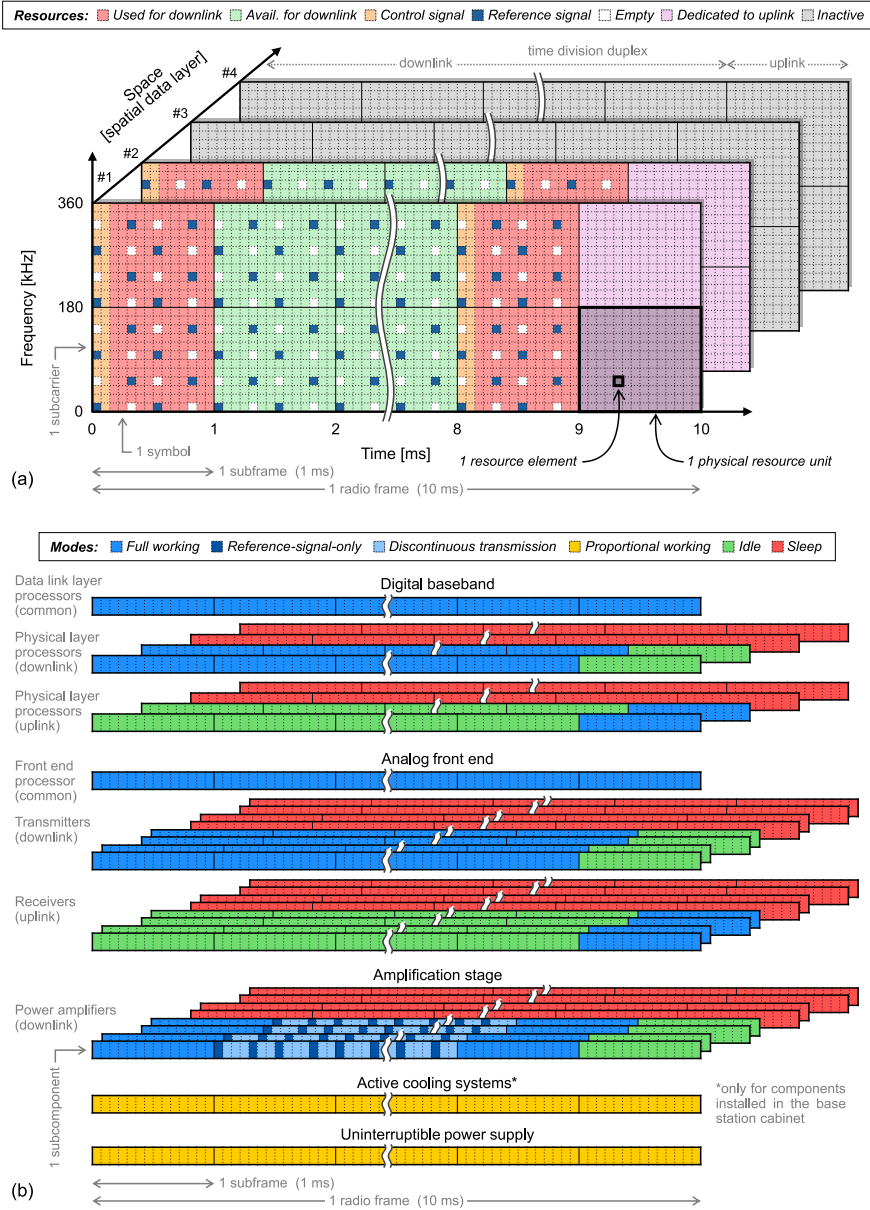


Fig. 5.9 Multi-state base station power model applied to one cell supporting time division duplex, 4 spatial data layers, and 8 transceivers and power amplifiers: (a) an example of partly loaded resource grid, and (b) the corresponding operating modes of all subcomponents. Half of the cell capacity is deactivated and the associated subcomponents are in sleep mode. All available resources are used at full transmit power in loaded subframes.

by scaling the reference power P_k^{ref} across S scaling variables as

$$P_k^{full}(\varphi) = P_k^{ref} \prod_{s=1}^S \left(\frac{\varphi_s}{\varphi_s^*} \right)^{\alpha_{k,s}}, \quad (5.33)$$

where the scaling variable s has an actual value φ_s , a reference value φ_s^* , and a subcomponent-specific scaling exponent $\alpha_{k,s}$. The model-agnostic reference situation for the scaling variables is defined by the reference frequency $f^* = 1$ GHz, reference bandwidth $B^* = 1$ MHz, and reference power $P^* = 1$ W. In this model, the reference power P_k^{ref} and the set of $\alpha_{k,s}$ are the technological parameters.

Intermediate working modes The power consumption of a subcomponent in an intermediate working mode (i.e., $m \in \{2, 3, \dots, M-1\}$) is modeled as a fraction of the full working power consumption, similar to [133, 134]. This yields

$$P_k^{(m)} = P_k^{full} \delta_k^{(m)}, \quad (5.34)$$

where $\delta_k^{(m)} \in [0, 1[$ represents the fraction of full working power consumption for subcomponent k in mode m . The number of working modes differs for each subcomponent and is chosen to enable the study of realistic BS behavior while preventing the overcomplication of the complete BS model. For consistency, power fractions must satisfy $\delta_k^{(M-1)} \leq \dots \leq \delta_k^{(2)} \leq 1$, as illustrated in Figure 5.8.

Idle mode The power consumption of a subcomponent in idle mode is modeled according to Equation (5.34) and satisfies $\delta_k^{idle} \leq \delta_k^{(M-1)}$.

Sleep mode The power consumption of a subcomponent in sleep mode is modeled according to Equation (5.34) and satisfies $\delta_k^{sleep} \leq \delta_k^{idle}$. To capture the slower transitions to and from sleep mode [43–45, 170, 175], the subcomponents are assumed not to switch between active modes and the sleep mode during a multi-frame period (with $T_f = 20$ ms by default).

Power saving strategies To reduce the BS power consumption, PSSs may be employed to adapt the active BS configuration to the actual load. For instance, PSSs can adjust the availability of physical resources in the time, frequency, and spatial domains. The unused subcomponents can then switch to sleep mode to consume less power. Typically, PSSs are categorized into four main types [43–46].

- *Time-domain* strategies involve deactivating subcomponents over time.
- *Frequency-domain* strategies involve deactivating one or more frequency bands and their associated processors, TRXs and PAs.
- *Spatial-domain* strategies involve deactivating one or more spatial data layers and their associated processors, TRXs and PAs.
- *Power-domain* strategies involve reducing the full transmit power of the PAs.

Additionally, the proposed power model considers PSSs at two time scales.

- *Fixed* strategies adapt the BS configuration at the hourly time scale based on a fixed daily profile of hourly average resource loads.
- *Dynamic* strategies adapt the BS configuration dynamically at the multi-frame time scale based on the actual short-term resource loads.

Thus, subcomponents subject to fixed PSSs remain in either active or sleep mode for one hour, while subcomponents subject to dynamic PSSs can switch between active and sleep modes once per multi-frame period (i.e., every 20 ms). Distinguishing between these two time scales is important for studying how the time response of PSSs affects the magnitude of achievable energy savings.

Among the N identical subcomponents contained in a BS component, the number of active subcomponents is denoted by $N^\diamond$, while the remaining $N - N^\diamond$ subcomponents are in sleep mode. When a subcomponent k is active, its average power consumption during the multi-frame period T_f is the average of its power levels $P_k^{(m)}$ over the M active modes. This power averaging is weighted by $\tau_{m,k}$, the ratio of time spent in mode m . Otherwise, the subcomponent consumes P_k^{sleep} while in sleep mode. For a BS component i comprising K types of subcomponents, the multi-frame power consumption at t_f is

$$P_i[t_f] = \sum_{k=1}^K \left(N_k^\diamond[t_f] \sum_{m=1}^{M_k} \tau_{m,k}[t_f] P_k^{(m)} + (N_k - N_k^\diamond[t_f]) P_k^{sleep} \right), \quad (5.35)$$

where M_k is the number of active modes for subcomponent k . When all modes of all subcomponents are modeled as in Equation (5.34), Equation (5.35) becomes

$$P_i[t_f] = \sum_{k=1}^K \left(P_k^{full} \cdot \left[N_k^\diamond[t_f] \sum_{m=1}^{M_k} \tau_{m,k}[t_f] \delta_k^{(m)} + (N_k - N_k^\diamond[t_f]) \delta_k^{sleep} \right] \right). \quad (5.36)$$

The proposed model neglects both the transition time delay between working modes and the energy overhead for subcomponent activation [43–45, 170, 175].

5.4.2 Digital baseband

The DBB performs the digital functions of the BS. Its multi-frame power consumption is assumed to be independent of the physical resource load, as shown in [131, 166]. The DBB is modeled by three types of subcomponent: the data link layer processors, the DL physical layer processors, and the UL physical layer processors.

Full working power consumption of subcomponents The total power consumption of data link layer processors for the entire BS scales with the total number of cells N_C . Since the DBB power consumption is expressed per cell in Equation (5.1),

an equal fraction of their total power consumption is allocated to each cell as

$$P_{link}^{full} = \frac{1}{N_C} P_{link}^{ref} \cdot (N_C)^{\alpha_{link}} \quad (5.37)$$

where P_{link}^{ref} and α_{link} are technological parameters.

For a given cell, the power consumption of physical layer processors is modeled per spatial data layer², scaling with the layer capacity reflected by the bandwidth B . Since the bandwidth is the same for DL and UL and their operations are symmetrical, the full working power of these processors is modeled identically in each direction as

$$P_{phy}^{full} = P_{phy}^{ref} \cdot \left(\frac{B}{B^*} \right)^{\alpha_{phy}} \quad (5.38)$$

where P_{phy}^{ref} and α_{phy} are technological parameters.

Multi-frame power consumption of subcomponents The data link layer processor is assumed to be always-on, such that it can reactivate the other components even when the BS is in full sleep. Thus, this processor continuously consumes P_{link}^{full} . Conversely, the power consumption of the physical layer processors depends on the activity of their spatial data layers. These processors are assumed to operate in three modes for each of the DL (resp. UL) spatial layer (see Figure 5.9):

- full working mode during the DL (resp. UL) time ratio τ_{DL} (resp. τ_{UL}),
- idle mode during the complementary time ratio $1 - \tau_{DL}$ (resp. $1 - \tau_{UL}$),
- or sleep mode when the layer is inactive.

The number of active spatial layers, denoted by $N_L^\diamond$, is assumed to be the same in the DL and UL. Note that $N_L^\diamond$ exceeds the number of multiplexed data streams in the cell when these streams are conveyed over multiple spatial layers to achieve spatial diversity or beamforming.

Using Equation (5.36), the multi-frame power consumption of the DL and UL physical layer processors are respectively

$$P_{phy,DL}[t_f] = P_{phy}^{full} \cdot \left[N_L^\diamond[t_f] \cdot \left(\tau_{DL} + (1 - \tau_{DL}) \delta_{phy}^{idle} \right) + \left(N_L - N_L^\diamond[t_f] \right) \delta_{phy}^{sleep} \right], \quad (5.39)$$

and

$$P_{phy,UL}[t_f] = P_{phy}^{full} \cdot \left[N_L^\diamond[t_f] \cdot \left(\tau_{UL} + (1 - \tau_{UL}) \delta_{phy}^{idle} \right) + \left(N_L - N_L^\diamond[t_f] \right) \delta_{phy}^{sleep} \right], \quad (5.40)$$

where N_L is the total number of spatial data layers, and δ_{phy}^{idle} and δ_{phy}^{sleep} are tech-

²In this thesis, a *spatial data layer* is defined as a physical channel able to convey up to one independent data stream. The fixed number of spatial data layers corresponds to the maximum number of data streams that can be spatially multiplexed within a cell.

nological parameters that respectively model the idle and sleep modes. These parameters are assumed to be identical for both physical layer processors. Since the DL and UL operate simultaneously in FDD (i.e., $\tau_{DL} = \tau_{UL} = 1$) and sequentially in TDD (i.e., $\tau_{DL} + \tau_{UL} = 1$), the idle mode only occurs in TDD. With dynamic PSSs, N_L° can be reconfigured at each multi-frame. When $N_L^\circ < N_L$, the available cell capacity is reduced, and thus $\max(\bar{x}[t_f]) < 1$.

Multi-frame power consumption of the component As a result, the multi-frame power consumption of the DBB is

$$P_{DBB}[t_f] = P_{link}^{full} + P_{phy,DL}[t_f] + P_{phy,UL}[t_f]. \quad (5.41)$$

5.4.3 Analog front end

The AFE performs analog TX and RX functions, as well as digital-to-analog and analog-to-digital conversion. As the DBB, its multi-frame power consumption is assumed to be independent of the physical resource load. The AFE is modeled by three types of subcomponents: a front end processor, transmitters in the DL, and receivers in the UL. Typically, there is one front end processor and multiple TRXs per cell. Without ABF, the number of TRXs is $N_{TRX} = N_L$, e.g., in traditional RUs. With ABF, $N_{TRX} > N_L$ in order to enable from beamforming, e.g., in AAUs.

Full working power consumption of subcomponents The full working power consumption of the front end processor scales with the bandwidth B and the maximum transmit power of the cell, denoted by P_{TX}^{cell} . The latter serves as a proxy for the size and complexity of the AFE, which is calculated as $P_{TX}^{cell} = N_{TRX} P_{TX}^{max}$. With an RFU, the AFEs for all sectors within a single band are combined into a single physical component installed in the BS cabinet, with a single front end processor per band. Thus, its full working power is divided by N_S in the power model, since it is expressed per cell in Equation (5.1). To account for the greater subcomponent complexity, P_{TX}^{cell} is multiplied by N_S for scaling. This yields

$$P_{proc}^{full} = \begin{cases} P_{proc}^{ref} \cdot \left(\frac{B}{B^*}\right)^{\alpha_{proc,B}} \left(\frac{P_{TX}^{cell}}{P^*}\right)^{\alpha_{proc,P}} & \text{if } \kappa_{RU} \in \{RRU, AAU\} \\ \frac{P_{proc}^{ref}}{N_S} \cdot \left(\frac{B}{B^*}\right)^{\alpha_{proc,B}} \left(\frac{N_S P_{TX}^{cell}}{P^*}\right)^{\alpha_{proc,P}} & \text{if } \kappa_{RU} = RFU \end{cases}, \quad (5.42)$$

where P_{proc}^{ref} , $\alpha_{proc,B}$ and $\alpha_{proc,P}$ are technological parameters.

Next, the full working power consumption of the transmitters and receivers scales with the bandwidth B and the maximum transmit power per PA P_{TX}^{max} , which

serves as a proxy for the size and complexity of the TRX chains. Since the scaling variables for the transmitters and receivers are the same and their operations are symmetrical, their full working power is modeled identically by

$$P_{TRX}^{full} = P_{TRX}^{ref} \cdot \left(\frac{B}{B^*} \right)^{\alpha_{TRX,B}} \left(\frac{P_{TX}^{max}}{P^*} \right)^{\alpha_{TRX,P}}, \quad (5.43)$$

where P_{TRX}^{ref} , $\alpha_{TRX,B}$ and $\alpha_{TRX,P}$ are technological parameters.

Multi-frame power consumption of subcomponents The front end processor is assumed to be always-on at full working power when the cell is active. Denoting respectively the number of supported and active bands in the AFE by N_B and $N_B^\diamond$, the multi-frame power consumption of this subcomponent is

$$P_{proc}[t_f] = P_{proc}^{full} \cdot \left[N_B^\diamond[t_f] + \left(N_B - N_B^\diamond[t_f] \right) \delta_{proc}^{sleep} \right], \quad (5.44)$$

where δ_{proc}^{sleep} is a technological parameter that model the sleep mode. Since the AFE is modeled per cell in Equation (5.1), $N_B = 1$. With dynamic PSSs, $N_B^\diamond$ can be reconfigured at each multi-frame. Typically, $N_B^\diamond[t_f] = \min \{1, N_L^\diamond[t_f]\}$.

The power consumption of the transmitters (resp. receivers) depends on their TX (resp. RX) activity in the DL (resp. UL). These subcomponents operate in the same three modes as the DBB physical layer processors (see Section 5.4.2), as shown in Figure 5.9. The number of active transmitters and receivers is assumed to be the same, denoted by $N_{TRX}^\diamond$. Using Equation (5.36), their multi-frame power consumption are respectively

$$P_{TXs}[t_f] = P_{TRX}^{full} \cdot \left[N_{TRX}^\diamond[t_f] \cdot \left(\tau_{DL} + (1 - \tau_{DL}) \delta_{TRX}^{idle} \right) + \left(N_{TRX} - N_{TRX}^\diamond[t_f] \right) \delta_{TRX}^{sleep} \right], \quad (5.45)$$

and

$$P_{RXs}[t_f] = P_{TRX}^{full} \cdot \left[N_{TRX}^\diamond[t_f] \cdot \left(\tau_{UL} + (1 - \tau_{UL}) \delta_{TRX}^{idle} \right) + \left(N_{TRX} - N_{TRX}^\diamond[t_f] \right) \delta_{TRX}^{sleep} \right], \quad (5.46)$$

where δ_{TRX}^{idle} and δ_{TRX}^{sleep} are technological parameters that are assumed to be identical for both subcomponents. As for the DBB, the idle mode of TRXs only occurs in TDD. With dynamic PSSs, $N_{TRX}^\diamond$ can be reconfigured at each multi-frame, typically maintaining the ratio $N_{TRX}^\diamond[t_f]/N_{TRX} = N_L^\diamond[t_f]/N_L$.

Multi-frame power consumption of the component As a result, the multi-frame power consumption of the AFE is

$$P_{AFE}[t_f] = P_{proc}[t_f] + P_{TXs}[t_f] + P_{RXs}[t_f]. \quad (5.47)$$

5.4.4 Amplification stage

The AS amplifies the RF signals before they are emitted by the antennas. This component is modeled by its constituent PAs, which are only used in TX for the DL. The number of PAs in the AS is assumed to be equal to N_{TRX} , the number of transmitters in the AFE. Similarly, the number of active PAs in a multi-frame is equal to $N_{TRX}^\circ[t_f]$, the number of active transmitters. As detailed in Section 5.3, the per-symbol PA power consumption varies with its per-symbol output power $P_{TX} \in [0, P_{TX}^{full}]$. Since P_{TX} depends primarily on the per-subframe load, the multi-frame power consumption of the AS is highly independent of the physical resource load, as observed for RUs in [131, 165, 211] and in Figure 5.1(a).

The full-load transmit power per PA can be set lower than its maximum transmit power, such that $P_{TX}^{full} \leq P_{TX}^{max}$. This enables MNOs to adjust the total transmit power of the cell to comply with regulations on electromagnetic field exposure [230], reduce inter-cell interference between nearby BSs, or reduce the BS energy consumption, either continuously or via fixed or dynamic PSSs. Furthermore, the transmit power of the reference signals per PA, denoted by P_{TX}^{sig} , is a fraction of P_{TX}^{full} proportional to the number of subcarriers carrying reference signals during that symbol, denoted by δ_{sig} . This power can be boosted by β_{RS} (in dB) to improve reference signal coverage. This yields

$$P_{TX}^{sig} = 10^{\frac{\beta_{RS}}{10}} \delta_{sig} P_{TX}^{full}. \quad (5.48)$$

By default, $\beta_{RS} = 3$ dB in order for the power not transmitted by the empty REs to be allocated to the reference signals. Thus, the transmit power per PA in a fully loaded symbol is P_{TX}^{full} while improving the reference signal coverage. Otherwise, the BS adjusts the transmit power of the other REs to ensure that the transmit power per PA remains P_{TX}^{full} in fully loaded symbols [231, 232].

Operating modes of subcomponents Since PAs are key subcomponents for the dynamic BS power consumption, their operating modes are modeled with finer granularity than for other subcomponents. Its operating modes consist of several working modes for subframes during which the DL is active, plus an idle mode and a sleep mode. To keep the number of working modes manageable, a single mode is considered when a subframe is used for DL. A loaded subframe in a cell is then assumed to use all available PRUs for DL, and thus the PA operates at full-load output

power P_{TX}^{full} . The per-subframe load of the k th PA is therefore $x_{PA}[k, t_{sf}] \in \{0, 1\}$. Assuming the multi-frame average load of the cell is evenly distributed across all active PAs, the multi-frame average load per PA is

$$\bar{x}_{PA}[t_f] = \bar{x}[t_f] \frac{N_{TRX}}{N_{TRX}^{\diamond}[t_f]}. \quad (5.49)$$

The proposed modeling approach is compatible with current BS operation under real data traffic patterns (see Appendix A.5). However, intermediate load levels could be considered in future works.

As shown in Figure 5.9, five operating modes are considered for the PAs:

- three working modes during the DL time ratio τ_{DL} :
 - full working mode with $P_{TX} = P_{TX}^{full}$ during a time ratio proportional to the multi-frame average PA load denoted by $\bar{x}_{PA}[t_f]$,
 - reference-signals-only mode with $P_{TX} = P_{TX}^{sig}$ during the time ratio $(1 - \bar{x}_{PA}[t_f])\tau_{sig}$, where τ_{sig} is the signaling time ratio (as the BS continues to transmit reference signals even when the cell is not loaded to enable upcoming UE connections),
 - discontinuous transmission (DTX) mode, such that $P_{TX} = 0$ during the complementary time ratio $(1 - \bar{x}_{PA}[t_f])(1 - \tau_{sig})$,
- idle mode during the complementary non-DL time ratio $1 - \tau_{DL}$,
- or sleep mode when the subcomponent is inactive.

Multi-frame power consumption of the component Using Equation (5.35), the multi-frame AS power consumption is the weighted sum of the PA power consumption $P_{PA}(P_{TX})$, modeled by Equation (5.31), in the five operating modes as

$$\begin{aligned} P_{AS}[t_f] = N_{TRX}^{\diamond}[t_f] \cdot & \left(\tau_{DL} \cdot \bar{x}_{PA}[t_f] P_{PA}(P_{TX}^{full}[t_f]) \right. \\ & + \tau_{DL} \cdot (1 - \bar{x}_{PA}[t_f]) \tau_{sig} P_{PA}(P_{TX}^{sig}[t_f]) \\ & + \tau_{DL} \cdot (1 - \bar{x}_{PA}[t_f]) (1 - \tau_{sig}) P_{PA}(0) \delta_{PA}^{dtx} \\ & \left. + (1 - \tau_{DL}) P_{PA}(0) \delta_{PA}^{idle} \right) \\ & + (N_{TRX} - N_{TRX}^{\diamond}[t_f]) P_{PA}(0) \delta_{PA}^{sleep}, \end{aligned} \quad (5.50)$$

where δ_{PA}^{dtx} , δ_{PA}^{idle} and δ_{PA}^{sleep} are technological parameters that respectively model the fraction of power consumed in DTX, idle, and sleep modes relative to $P_{PA}(0)$ (unlike other subcomponents for which they relate to full working mode). With dynamic PSSs, $N_{TRX}^{\diamond}$, P_{TX}^{full} and P_{TX}^{sig} can be reconfigured at each multi-frame.

5.4.5 Active cooling systems

The ACSs dissipate the heat generated by the other BS components. ACSs are modeled separately for each BS component with a proportional power consumption overhead $\epsilon_{cool}^{(i)}$ as in [169–171], yielding

$$P_{ACS}^{(i)} = \epsilon_{cool}^{(i)} P_i. \quad (5.51)$$

Then, the total consumption of component i including ACS is

$$P_i + P_{ACS}^{(i)} = \frac{P_i}{\eta_{cool}^{(i)}}, \quad (5.52)$$

where $\eta_{cool}^{(i)} = 1/(1 + \epsilon_{cool}^{(i)}) \leq 1$ represents the cooling efficiency. The cooling efficiency factors for the DBB, AFE, and AS are respectively

$$\eta_{cool}^{DBB} = \eta_{cool}, \quad (5.53)$$

and

$$\eta_{cool}^{AFE} = \eta_{cool}^{AS} = \begin{cases} \eta_{cool} & \text{if } \kappa_{RU} = \text{RFU} \\ 1 & \text{if } \kappa_{RU} \in \{\text{RRU}, \text{AAU}\} \end{cases}, \quad (5.54)$$

where η_{cool} is a technological parameter assumed to be identical for all components, and κ_{RU} is a BS configuration variable that determines the RU type. The DBB installed in the BS cabinet always requires an ACS, whereas the AFE and AS implemented by a RU installed outside the cabinet (i.e., a RRU or an AAU) do not require an ACS because they rely on passive heat dissipation only.

5.4.6 Uninterruptible power supply

The UPS delivers stable electrical power to all active components of the BS. It is modeled once for the entire BS (see Equation 5.1) with a proportional power consumption overhead ϵ_{supply} as in [169–171], yielding

$$P_{UPS} = \epsilon_{supply} P'_{BS}, \quad (5.55)$$

where P'_{BS} is the BS power consumption excluding the UPS. Then, the total BS power consumption including UPS is

$$P_{BS} = P'_{BS} + P_{UPS} = \frac{P'_{BS}}{\eta_{supply}}, \quad (5.56)$$

where $\eta_{supply} = 1/(1 + \epsilon_{supply}) \leq 1$ is a technological parameter representing the power supply efficiency. This parameter models both the efficiency of the power converters and the power losses within the backup batteries.

5.4.7 Hourly average power consumption

The total BS power consumption is the sum of the power consumed by all its components. At the multi-frame level, Equation (5.1) can be rewritten as

$$P_{BS}[t_f] = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_c} \left(\frac{P_{DBB,c}[t_f]}{\eta_{cool,c}^{DBB}} + \frac{P_{AFE,c}[t_f]}{\eta_{cool,c}^{AFE}} + \frac{P_{AS,c}[t_f]}{\eta_{cool,c}^{AS}} \right). \quad (5.57)$$

Using Equation (5.2) and denoting the average hourly power consumption of the DBB, AFE, and AS as respectively $\bar{P}_{DBB}[t_h]$, $\bar{P}_{AFE}[t_h]$, and $\bar{P}_{AS}[t_h]$, the average hourly power consumption of the BS becomes

$$\bar{P}_{BS}[t_h] = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_c} \left(\frac{\bar{P}_{DBB,c}[t_h]}{\eta_{cool,c}^{DBB}} + \frac{\bar{P}_{AFE,c}[t_h]}{\eta_{cool,c}^{AFE}} + \frac{\bar{P}_{AS,c}[t_h]}{\eta_{cool,c}^{AS}} \right), \quad (5.58)$$

which can be used in Equation (5.3) to compute the hourly BS energy consumption.

Without power saving strategy Without PSS, each BS cell is configured with $N_L^\diamond[t_f] = N_L$, $N_B^\diamond[t_f] = N_B$, $N_{TRX}^\diamond[t_f] = N_{TRX}$, and $P_{TX}^{full}[t_f] = P_{TX}^{max}$. First, this implies that $P_{DBB}[t_f]$ and $P_{AFE}[t_f]$ are constant over time, with static average power consumption denoted by P_{DBB}^{max} and P_{AFE}^{max} , respectively. Second, this indicates that the AS is configured to transmit the RF signal with the maximum output power P_{TX}^{max} at full load. Consequently, the hourly average power consumption of the AS varies linearly with the hourly average resource load $\bar{x}$ as

$$\bar{P}_{AS}^{max}(\bar{x}) = P_{AS}^{stat} + \bar{x} \cdot P_{AS}^\Delta, \quad (5.59)$$

where P_{AS}^{stat} is the average static power of the AS, and P_{AS}^Δ is the average load-proportional factor. From Equation (5.50), these two terms are

$$P_{AS}^{stat} = N_{TRX} \cdot \left(\tau_{DL} \tau_{sig} P_{PA}^{sig} + P_{PA}^0 \cdot \left(\tau_{DL} \cdot (1 - \tau_{sig}) \delta_{PA}^{dtx} + (1 - \tau_{DL}) \delta_{PA}^{idle} \right) \right), \quad (5.60)$$

and

$$P_{AS}^\Delta = N_{TRX} \cdot \left(\tau_{DL} P_{PA}^{max} - \tau_{DL} \tau_{sig} P_{PA}^{sig} - \tau_{DL} \cdot (1 - \tau_{sig}) P_{PA}^0 \delta_{PA}^{dtx} \right), \quad (5.61)$$

where P_{PA}^{max} , P_{PA}^{sig} , and P_{PA}^0 denote respectively the PA power consumption at P_{TX}^{max} , $P_{TX} = 10^{\frac{\bar{P}_{BS}}{10}} \delta_{sig} P_{TX}^{max}$, and $P_{TX} = 0$. This demonstrates that lowering δ_{PA}^{idle} reduces the static power of the AS, and that lowering δ_{PA}^{dtx} additionally makes its average power consumption more proportional to the load. Reducing the rate and transmit power of reference signals also decreases the average power consumed by the AS and makes it more proportional to the load. However, this strategy may compromise the ability of UEs to identify and connect to the BS.

Without PSS and assuming that the average load is the same for all BS cells, the hourly average BS power consumption given by Equation (5.58) becomes

$$\bar{P}_{BS}(\bar{x}) = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_C} \left(\frac{P_{DBB,c}^{max}}{\eta_{cool,c}^{DBB}} + \frac{P_{AFE,c}^{max}}{\eta_{cool,c}^{AFE}} \right) + \frac{\bar{x}}{\eta_{supply}} \sum_{c=1}^{N_C} \frac{P_{AS,c}^{\Delta}}{\eta_{cool,c}^{AS}}. \quad (5.62)$$

Here, $\bar{P}_{BS}$ is linear with respect to the hourly average load, consistent with on-site measurements in Figure 5.1(a) and previous studies [131, 167, 169, 190, 211].

With fixed power saving strategies The average hourly power model for a BS with fixed PSSs can be obtained by rewriting Equation (5.62) as

$$\bar{P}_{BS}(\bar{x}) = P_{BS}^{stat} + \bar{x} \cdot P_{BS}^{\Delta}, \quad (5.63)$$

where P_{BS}^{stat} is the static BS power without PSS, and P_{BS}^{Δ} is the the corresponding average load-proportional factor. For a given PSS s , the static BS power becomes

$$P_{BS}^{stat,(s)} = P_{BS}^{stat} \delta_{BS}^{(s)} = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_C} \left(\frac{P_{DBB,c}^{max}}{\eta_{cool,c}^{DBB}} + \frac{P_{AFE,c}^{max}}{\eta_{cool,c}^{AFE}} \right) \delta_{BS}^{(s)}, \quad (5.64)$$

where $\delta_{BS}^{(s)} \in [0, 1]$ represents the corresponding fraction of the static power of the fully active BS. Then, the average load-proportional factor for this sth PSS becomes

$$P_{BS}^{\Delta,(s)} \leq P_{BS}^{\Delta} = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_C} \frac{P_{AS,c}^{\Delta}}{\eta_{cool,c}^{AS}}. \quad (5.65)$$

If the PSS does not affect the full transmit power of active PAs, then $P_{BS}^{\Delta,(s)} = P_{BS}^{\Delta}$. Consequently, the BS power model with such fixed PSS remains linear with the same slope as without PSS, but shifted downward due to the lower static power. Yet, the maximum achievable load becomes < 1 because the available BS capacity is reduced as part of the physical resources are deactivated. However, if a fixed PSS deactivates entire bands, the average load is no longer the same for all cells because the inactive cells remain unloaded. In this case, the average power model becomes a discontinuous multilevel model consisting of successive linear models.

In full sleep mode, the static BS power consumption becomes

$$P_{BS}^{sleep} = \frac{1}{\eta_{supply}} \sum_{c=1}^{N_C} \left(\frac{P_{link,c}^{full} + 2N_{L,c} P_{phy,c}^{full} \delta_{phy}^{sleep}}{\eta_{cool,c}^{DBB}} + \frac{P_{proc,c}^{full} \delta_{proc}^{sleep} + 2N_{TRX,c} P_{TRX,c}^{full} \delta_{TRX}^{sleep}}{\eta_{cool,c}^{AFE}} + \frac{N_{TRX,c} P_{PA,c}^0 \delta_{PA}^{sleep}}{\eta_{cool,c}^{AS}} \right), \quad (5.66)$$

and the load-proportional factor becomes

$$P_{BS}^{\Delta, sleep} = 0. \quad (5.67)$$

This indicates that the minimum energy consumption of the BS is affected by four configuration variables: the number of sectors N_S and bands N_B that determine the number of cells N_C , the number of spatial data layers N_L , and the number of TRXs N_{TRX} , as well as by various technological parameters, notably δ_{phy}^{sleep} , δ_{proc}^{sleep} , δ_{TRX}^{sleep} , and δ_{PA}^{sleep} . Since all BS capacity is deactivated in full sleep mode, communication is impossible, and thus $\bar{x} = 0$.

With dynamic power saving strategies Due to BS reconfigurations at the multi-frame time scale, it is difficult to obtain a closed-form expression for the hourly average power consumption of a BS implementing dynamic PSSs. Unlike with fixed PSSs, the relationship between power consumption and average resource load is typically nonlinear with dynamic PSSs, varying from the full sleep power P_{BS}^{sleep} to the maximum BS power $P_{BS}^{max} = P_{BS}^{stat} + 1 \cdot P_{BS}^{\Delta}$. This behavior is illustrated with empirical measurements in Section 5.5 and further discussed in Chapter 7.

5.5 Technological parameter estimation

Using the approach explained in Section 4.4, the technological parameters of the BS power consumption model are estimated via regression analysis of empirical data. The goal of this approach is to provide realistic, albeit approximate, numerical values for enabling quantitative comparisons of power consumption between different BS configurations. Based on the complete set of empirical data sources described in Section 4.4.2, this section first presents the specific dataset used to estimate the parameters of the BS power model. Then, it lists the obtained numerical parameter estimates and compares selected model predictions with corresponding empirical data. Finally, the section quantifies the uncertainties in the calibrated power models. Unlike the BS power model definition, technological parameter estimation relies on the physical representation of the BS architecture.

5.5.1 Specific empirical dataset

Two main sources of empirical data are used to estimate the technological parameters of the BS power model: on-site measurements from MNOs and technical documentation from manufacturers. On-site measurements reflect the actual power consumption of deployed BS components across a realistic range of physical resource loads. However, analyzing the raw measurements is time-consuming. Technical documentation, in contrast, is available for a broader range of commercial compo-

nent configurations and is easier to analyze thanks to standardized reporting. Yet, technical documentation is not guaranteed to accurately reflect power consumption in practice. Reported power consumption values are also limited to a small number of reference load levels, which may lack the granularity necessary to estimate all technological parameters. Therefore, combining the two data sources leverages their complementary strengths. For this thesis, on-site measurements were obtained for two macro BS in Belgium over a one-week period in 2023, and the collected documentation covers more than 100 BS components.

Using measurements from one of the two examined BSs, Figure 5.10 shows the relationship between average power consumption and average physical resource load for the different physical components. The studied BS is deployed in a large city and is equipped with two three-sector RFUs supporting 4G-LTE at 0.8 GHz and 5G-NR at 0.7 GHz (see Figure 5.10(b)), three dual-band RRUs supporting 4G-LTE at 1.8 and 2.1 GHz (see Figure 5.10(c)), and three AAUs supporting 5G-NR at 3.5 GHz (see Figure 5.10(d)). Note that measurements for one AAU are lacking. A single BBU supports its 15 cells (i.e., five frequency bands over three sectors), for a total capacity of 1 GHz per sector (see Figure 5.10(a)). Actually, this BS is shared by two MNOs, meaning that each cell supports two frequency carriers (one per MNO). Thus, the actual bandwidth and transmit power of each band is doubled, as indicated by "($\times 2$)" in Figure 5.10.

On top of the on-site measurements, Figure 5.10 plots the power consumption data reported in the technical documentation of the corresponding BS components. For the BBU, a single "typical" power consumption value is reported, as it is specified that it barely varies with the load. On-site measurements confirm this behavior, which aligns with the BS power model and Equation (5.62). For RUs, the technical documentation reports three or four operating points. Figure 5.10 also depicts linear fits derived from these data points with the $\pm 10\%$ error margin specified in the documentation. On-site measurements confirm that the average RU power consumption varies nearly linearly with the resource load above a certain load level, consistent with the BS power model and Equation (5.62).

Overall, Figure 5.10 shows that the linear behavior of the measurements aligns well with the linear fits based on the documentation data. This suggests that supplementing on-site measurements with technical documentation is a reliable approach for estimating technological parameters. However, the technical documentation does not reflect the nonlinear behavior observed in RU measurements at low and no loads. Since the linear behavior of the power consumption corresponds to fully active RUs without PSS, its nonlinear behavior is attributed to PSSs that dynamically adapt the active RU configuration to the actual load. Additionally, the measurements show that the examined BBU does not benefit from sleep mode. Therefore, empirical measurements are necessary to model commercially available PSSs. Conversely, the power consumption of BS components is rarely measured at full load (i.e., 1) under normal usage conditions, particularly in 5G-NR RUs that

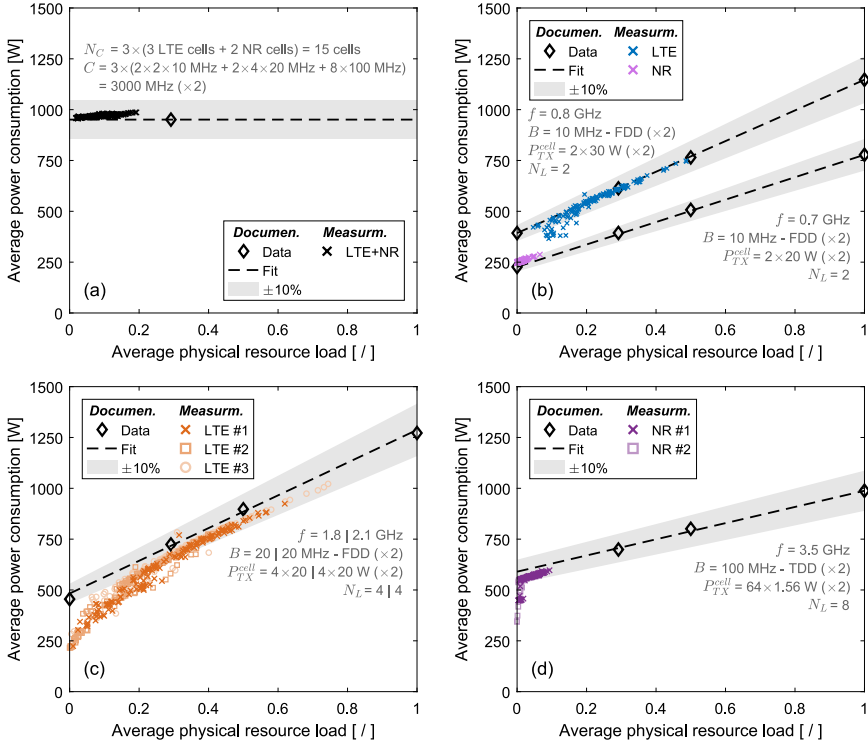


Fig. 5.10 Average power consumption vs. physical resource load for a macro base station shared by two operators: (a) the baseband unit, (b) two three-sector radio frequency units, (c) three dual-band remote technical units, and (d) two active antenna units. Hourly on-site measurements align with technical documentation data, except for nonlinearity at low load.

were lightly loaded in 2023 (i.e., < 0.1). Therefore, a key advantage of technical documentation is that it reports the full-load power consumption, which is useful for calibrating the power model over its full load range.

Regression analysis is then used to obtain numerical parameters estimates from this empirical dataset. Since all BS components in this dataset were still available on the market in 2023, they are assumed to belong to the same technological generation. For the regression analysis, the dataset is divided into three categories of physical BS components: BBUs, traditional RUs and AAUs. Two issues then arise. First, the proposed power model allows for numerous possible BS configurations but the dataset has limited diversity in component configurations. Second, some technological parameters relate to the per-symbol power model but these parameters are intended to be estimated based on average power consumption data only. To address these issues and ensure meaningful regression results, the domain

of possible solutions is constrained by limiting the possible scaling exponents of Equation (5.33) to $\alpha \in \{0, 0.25, 0.5, 0.75, 1\}$.

5.5.2 Numerical parameter estimates

The numerical estimates for the technological parameters of the BS power consumption model are provided in Table 5.2. This table also identifies the specific empirical data sources and literature references used to estimate each parameter.

For the DBB, P_{link}^{full} and P_{phy}^{full} scale respectively with the square root of N_C and linearly with B . For the AFE, P_{proc}^{full} scales according to the fourth root of P_{TX}^{cell} and does not actually vary with B . In contrast, P_{TRX}^{full} scales according to the square root of both B and P_{TX}^{max} . This underlines the importance of considering nonlinear parametric models. In addition, P_{proc}^{ref} is lower for AAUs than for RFUs and RRUUs, while P_{TRX}^{ref} is identical for both AAUs and traditional RUs. Thus, similar subcomponents may have different reference power values due to variations in the physical design of the BS component. Unlike other parameter estimates, the efficiencies of active cooling and power supply are estimated based solely on the literature because no empirical data were obtained for the ACSs and UPS. Accordingly, these numerical estimates are considered more uncertain. The communication protocol parameters are also estimated based solely on 4G-LTE and 5G-NR standards and are likely to evolve in future generations of mobile communications.

Table 5.2 also provides numerical parameter estimates for modeling different architectures and technologies of PAs in the AS. The Doherty architecture is considered typical for PAs in traditional RUs operating at carrier frequencies of 0.8-2.6 GHz with a maximum transmit power of 20-80 W. In contrast, the Class-AB architecture is considered typical for PAs operating with a maximum transmit power of 1-20 W (e.g., in AAUs and micro RUs). Additionally, LDMOS is assumed to be used in traditional RUs, GaN in AAUs at 3.5 GHz and GaAs in low-frequency micro RUs. Using the generalized PA model expressed by Equation (5.31), PA-related parameters are obtained by assuming a typical 8 dB PAPR and a normalized static power of $\xi = 0.04$. The resulting values of η_{max} for the examined PA configurations (between 0.29 and 0.47) are consistent with those reported in [137, 172, 227, 228]. The associated parameters ξ_{PA} and n also vary with the architecture, but not the semiconductor technology. Yet, the PA parameter estimates may differ for other architectures, semiconductor technologies, and PAPRs. Notably, reducing the PAPR of transmit RF signals would increase the effective PA efficiency.

In principle, combining the AFE and AS of multiple frequency bands into a single platform to form a multi-band RU could reduce the power consumption per cell through mutualization. However, empirical data reveals no significant difference in power consumption allocated per band between single-band RUs and the corresponding multi-band RUs. Therefore, the per-cell parametric power model is

Table 5.2 Technological parameter estimates for the power consumption model

Parameter	Estimate ^a	Unit	Sources ^b
<i>Digital baseband</i>			
$\{P_{link}^{ref}, P_{phy}^{ref}\}$	{90, 0.07}	W	● ○ △
$\{\alpha_{link}, \alpha_{phy}\}$	{0.5, 1}	/	● ○ △ [170, 173]
$\{\delta_{phy}^{idle}, \delta_{phy}^{sleep}\}$	{~0.75, ~0.75}	/	○ [44, 170]
<i>Analog front end</i>			
P_{proc}^{ref}	22 (RFU/RRU) 17 (AAU)	W	● ○
$\{\alpha_{proc,B}, \alpha_{proc,P}\}$	{0, 0.25}	/	● ○ [170, 173]
P_{TRX}^{ref}	0.18 (RFU/RRU) 0.18 (AAU)	W	● ○
$\{\alpha_{TRX,B}, \alpha_{TRX,P}\}$	{0.5, 0.5}	/	● ○ [170, 173]
$\{\delta_{proc}^{sleep}, \delta_{TRX}^{idle}, \delta_{TRX}^{sleep}\}$	{0.75, 1, 0.5}	/	● ○ [44, 170]
<i>Amplification stage</i>			
η_{max}	0.47 (Doherty, LDMOS, 40 W, 0.8 GHz) 0.33 (Doherty, LDMOS, 40 W, 1.8 GHz) 0.33 (Doherty, LDMOS, 20 W, 2.6 GHz) 0.30 (Class-AB, GaN, 3.125 W, 3.5 GHz) 0.29 (Class-AB, GaAs, 5 W, 1.8 GHz)	/	Section 5.3
ξ_{PA}	0.17 (Doherty) 0.10 (Class-AB)	/	Section 5.3
n	0.6 (Doherty) 0.5 (Class-AB)	/	Section 5.3
$\{\delta_{PA}^{dtx}, \delta_{PA}^{idle}, \delta_{PA}^{sleep}\}$	{1, 0.25, 0}	/	● ○ [44, 170]
<i>Active cooling systems</i>			
η_{cool}	~0.9	/	[170]
<i>Uninterruptible power supply</i>			
η_{supply}	~0.95	/	[170, 233]
<i>Protocol</i>			
τ_{DL}	1.00 (FDD) 0.75 (TDD)	/	[159, 160]
τ_{UL}	1.00 (FDD) 0.25 (TDD)	/	[159, 160]
τ_{sig}	4/14 (4G-LTE) 4/14/20 (5G-NR)	/	[159, 160]
δ_{sig}	2/12 (4G-LTE) 3.6/B (5G-NR)	/	[159, 160]

^a Estimates with higher uncertainty indicated with a "~".^b ● = on-site measurements, ○ = technical documentation, and △ = practical network configuration.

assumed to apply to both single- and multi-band RUs. In practice, the use of multi-band RUs appears to be primarily motivated by cost-cutting considerations and by easier and faster on-site installation and dismantling for MNOs.

Regarding idle and sleep modes, a consistency-related constraint is $\delta^{idle} \geq \delta^{sleep}$. For PAs, an additional constraint is $\delta_{PA}^{dtx} \geq \delta_{PA}^{idle}$. The numerical values for these power fractions are determined based on on-site measurements and on [43–45, 170, 175, 234]. Table 5.2 shows that, e.g., DTX is not used to reduce the PA working power at the per-symbol time scale, whereas the idle mode at the per-subframe time scale reduces the PA power by 75%, and the sleep mode at the multi-frame time scale completely eliminates static PA power consumption. Figure 5.11 shows that these values are consistent with on-site measurements. However, the estimated power fractions only represent current PSSs implemented by MNOs in Belgium, though improved PSSs are expected to perform better.

5.5.3 Predictions against measurements

A preliminary evaluation of the calibrated power model can be obtained by comparing selected model predictions with the corresponding empirical data. To this end, Figure 5.11 compares the power consumption predictions with the hourly on-site measurements for the three dual-band RRUs examined in Figure 5.10(c). Focusing on these specific components also illustrates how the simulated PSSs compare with those implemented in practice.

Figure 5.11 first depicts the calibrated average power model for different combinations of fixed PSSs providing $\{1, 0.75, 0.5, 0.25, 0\}$ of total capacity. These PSSs are categorized by their number of active PAs, and a given number of active PAs can support different levels of active capacity. For instance, reducing the total RU capacity to 0.5 can also be achieved either by deactivating entirely one of the two bands, deactivating one carrier per band (i.e., the two half-bands occupied by an MNO), or by deactivating two spatial data layers per carrier for both bands. This results in fewer active front end processors, TRXs and PAs, or a decrease in P_{TX}^{PA} , or a combination of these different factors. Thus, for a given active capacity, the RRU consumes less power when fewer PAs are active, even if they are more heavily loaded individually. For the studied RRUs, deactivating two TRX plus PAs saves around 50 W. Then, Figure 5.11 superimposes the hourly on-site measurements onto the model predictions. Since the actual PSS implemented in the examined RRUs adapt dynamically faster than the hourly measurement interval, the measurements are grouped by ranges of average active capacity over this interval.

Comparing the model predictions with the on-site measurements reveals that the proposed model matches the actual power consumption of the examined RUs. However, this comparison also shows that considering only fixed PSSs produces strictly linear power consumption models that do not reflect the nonlinear behavior observed in the measurements at low loads. Therefore, to accurately simulate the

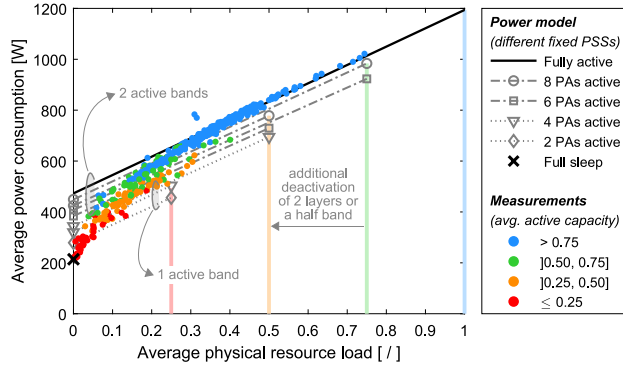


Fig. 5.11 Comparison of empirical and simulated relationships between average power consumption and average resource load for the three dual-band remote radio units examined in Figure 5.10(c). The calibrated power model with fixed power saving strategies (PSSs) aligns with the hourly on-site measurements grouped by average active capacity ranges.

power consumption of these commercial RUs, dynamic PSSs should be considered instead of fixed PSSs. Furthermore, deeper sleep modes and more advanced PSSs could be considered to simulate next-generation RUs.

5.5.4 Uncertainty quantification

As introduced in Section 4.4.3, lognormal distributions are used in the integrated RAN model to represent uncertainty. This uncertainty consists of two parts: variability in the empirical data, and potential error introduced by the proposed modeling approach. For each BS subcomponent, the variability part of the uncertainty in power consumption is quantified based on the spread of residuals from the regression analysis. To calculate the associated GSD, a lognormal distribution is fitted to the normalized residuals relative to the predicted power consumption, setting the median of the distribution to 1. Next, the error part is quantified by estimating a multiplicative error factor based on authors' judgments. In practice, error factors of 1.25 and 2 represent respectively high and medium confidence levels, with corresponding GSDs of $\sqrt{1.25} = 1.12$ and $\sqrt{2} = 1.41$.

Table 5.3 provides the GSDs representing uncertainty in the power model for each BS component. These factors are first presented separately for the variability and error parts of uncertainty, in order to distinguish statistically calculated GSDs from GSDs based on authors' judgments. Then, the total GSD is calculated from the GSDs of both parts, as explained in Section 4.4.3. As estimated in [CP2], the GSD of variability in the AFE and AS models is approximately 1.16 (i.e., an IQR from -10% to $+11\%$), while it is around 1.22 for the DBB (i.e., an IQR from -13% to $+14\%$). This reasonable degree of uncertainty is tolerated to keep the analytical

Table 5.3 Geometric standard deviations of power consumption model uncertainties

Base station component	Variability	Error ^a	Total
Digital baseband	1.22	1.12	1.26
Analog front end	1.16	1.12	1.21
Amplification stage	1.16	1.12	1.21
Active cooling systems	-	1.41	1.41
Uninterruptible power supply	-	1.41	1.41

^a Based on authors' judgments.

power model simple and based on interpretable parameters. However, variability GSDs cannot be quantified for components lacking a primary data source.

Since the datasets used to calibrate the DBB, AFE, and AS models are extensive and representative of their target scope, there is high confidence in the proposed power models for these components. This yields error GSDs of 1.12. Conversely, confidence in models lacking a primary data source is lower, yielding error GSDs of 1.41 for ACSs and UPS. As a result, ACSs and UPS exhibit the highest total GSD, AFE and AS the lowest, and DBB is in between. Although the power models for the DBB, ACSs and UPS are more uncertain, this is less critical than for the AFE and AS because they represent a smaller share of the total BS power consumption.

5.6 Results for typical configurations

This section illustrates the application of the BS power consumption model to the five typical BS configurations identified in Section 4.5. It first presents and compares the resulting power consumption for these configurations, and then performs an analysis of the associated uncertainties. All typical configurations examined in this section correspond to single-band BSs. In practice, however, most BSs deployed in RANs support multiple frequency bands. As a first approximation, the power consumption of a multi-band BS can therefore be obtained by summing the power consumption of the corresponding single-band configurations. This approximation is justified by the BS modeling approach, in which each cell is represented independently, except for the link layer boards in DBB, whose power consumption scales with the total number of cells. Further examination of the power consumption of multi-band BS configurations in relation to the QoS is provided in Chapter 7 for different network configurations and usage conditions.

5.6.1 Cross-configuration analysis

The calculated average power consumption of the typical BS configurations is presented in Figure 5.12 for three operating modes: (i) full sleep, (ii) fully active at no load (representing the static power consumption), and (iii) fully active at full load.

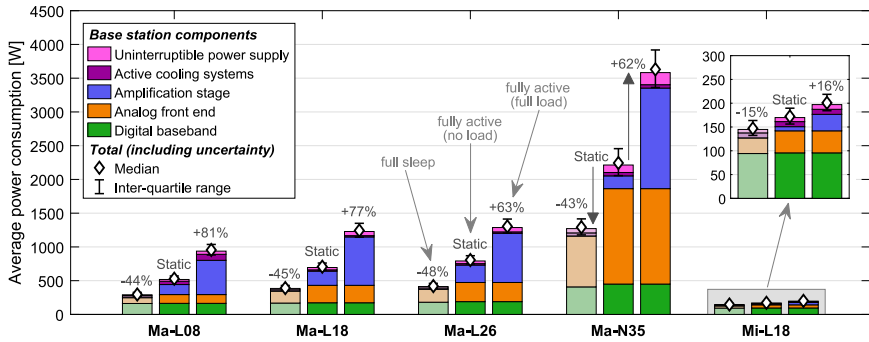


Fig. 5.12 Total average power consumption for five typical base station configurations in full sleep, fully active at no load, and fully active at full load. Total power consumption is broken down by component, and overall uncertainty is represented by the median and inter-quartile range of the underlying distribution. The quality of service provided by each configuration differs and must be considered when comparing them.

These power consumption results are also broken down by BS component. Before further analysis, it is important to note that the five typical configurations do not provide the same capacity or transmit power per cell. Therefore, they do not provide identical QoS in terms of data throughput per UE and coverage. In particular, the *Mi-L18* configuration is primarily intended for dense urban deployments, with approximately $\times 10$ -20 the density of macro BSs.

The total average power consumption is similar for the *Ma-L18* and *Ma-L26* configurations: about 700-800 W for static power and 1250-1300 W for full load power. This similar power consumption is due to the same total transmit power (i.e., 80 W per cell), while the $\times 2$ number of spatial data layers, TRXs, and PAs in *Ma-L26* is mostly offset by the reduction in transmit power per TX chain that reduces the power consumption per TRX and PA. The $\times 2$ capacity of *Ma-L26* compared to *Ma-L18* (i.e., 2×20 MHz and 4×20 MHz per cell, respectively) is reflected in an increase in DBB power of only 20 W.

The *Ma-L08* configuration consumes less power than *Ma-L18* and *Ma-L26*: 530 W of static power and 950 W of full load power. This is primarily due to the use of a lower carrier frequency, which increases the PA efficiency and reduces the AS power consumption by 200 W compared to *Ma-L18* (for the same transmit power of 80 W per cell). Second, using an RFU mutualizes the RUs of the three sectors into a single physical component, thus reducing the AFE power consumption by 130 W. However, this is partially offset by the ACS, which adds 70 W at full load to cool the RFU installed in the BS cabinet. The DBB power consumption is also reduced by 10 W due to the $\times 1/2$ total capacity (i.e., 2×10 MHz per cell).

The most recent 5G-NR configuration, *Ma-N35*, which supports 64T64R AAUs, consumes around $\times 3$ the power of the three typical 4G-LTE configurations with

traditional RUs: 2200 W of static power and 3600 W of full load power. This increase in power consumption primarily stems from the $\times 5$ power of AFEs due to their 64 TRXs per cell, although each TRX consumes less power individually. The total AS power consumption is higher because the total transmit power is 200 W per cell with a lower PA efficiency due to the Class-AB architecture and a higher carrier frequency. The DBB power consumption is also $\times 2.5$ compared to *Ma-L26*, for $\times 10$ the capacity (i.e., 8×100 MHz per cell).

Lastly, the microcell *Mi-L18* configuration consumes significantly less power than other macrocell configurations: 170 W of static power and 200 W of power at full load. In this configuration, the DBB accounts for $> 50\%$ of total power consumption. In contrast, the DBB accounts for only 15-25% of total power consumption in fully active macro configurations.

In all configurations, PAs of the AS induce most of the load-dependent power consumption, along with the ACSs and UPS. When fully active, the power consumption of macro BSs at full load is $+62\%$ to $+81\%$ the static power at no load. The AS dominates their full-load power consumption, except for *Ma-N35*, where it represents 40% of total power. In full sleep, the power consumption is -43 to -48% the static power of macro BSs, resulting in a full-sleep power range from 270 W for *Ma-L08* to 1300 W for *Ma-N35*. In contrast, the full-load and full-sleep power levels of *Mi-L18* are respectively $+16\%$ and -15% its static power, as the AS accounts for a smaller share of its total power consumption. Note that these results reflect the performance of sleep modes implemented in RANs operating in Belgium in 2023. Yet, further improvements to sleep modes could reduce the full-sleep power consumption of BSs, especially regarding the TRXs in AFEs and the DBB.

5.6.2 Uncertainty analysis

The overall uncertainty in total BS power consumption is calculated using Monte Carlo simulations. In these simulations, uncertainties of different BS components (e.g., AFE and AS) are assumed to be independent, whereas uncertainties of the same type of components (e.g., all AFEs) are assumed to be fully correlated. Consequently, when stochastic assessments are summed across all components, random deviations partially cancel out, resulting in an overall distribution with a narrower relative spread than that of the components taken individually. For example, combining two different components with GSDs of 1.20 yields an overall GSD of about 1.13. However, if component uncertainties were assumed to be correlated, the overall GSD would remain at 1.20. In Figure 5.12, the power consumption assessments exhibit a consistent IQR of -8% to $+9\%$ with respect to the median (i.e., the "most representative" value in lognormal distributions), regardless of configuration or operating mode. This IQR corresponds to an overall GSD of 1.13, which is smaller than GSDs for total uncertainty of individual BS components.

5.7 Model validation

As introduced in Section 4.5, model validation aims to qualitatively evaluate the accuracy of the proposed models. For the BS power model, validation involves comparing the predicted power consumption for specific BS configurations with corresponding empirical data from an independent validation set. The validation set should capture a representative diversity of BS configurations deployed in real networks and their varying operating conditions. Moreover, it must not have been used for model development or calibration. Accordingly, 32 BSs were randomly selected from one RAN in Belgium across deployment areas with different population densities. Thirty of these samples are macrocell BSs with three sectors (i.e., $N_S = 3$), while the remaining two are omnidirectional microcell BSs (i.e., $N_S = 1$) deployed in data traffic hotspots. In practice, the validation set consists of hourly on-site measurements taken over a one-week period in 2023.

Figure 5.13 compares the power consumption predicted by the BS power model with the corresponding validation data for typical RU configurations. Here, the full transmit power per cell varies for each typical configuration. For the static power, Figure 5.13(a) shows that the validation data for *Ma-L08* and *Ma-L26* generally falls within the IQR of predictions. However, the static power for *Ma-L18* is slightly overestimated, particularly for RUs with high transmit power, and the static power for *Mi-L18* is underestimated for RUs with low transmit power. The static power of *Ma-N35* is also slightly underestimated. Overall, the model accurately predicts RU power consumption in full sleep. Figure 5.13(b) shows the predicted and observed RU power efficiency at full transmit power (i.e. total transmit power per cell at full load divided by the corresponding RU power consumption). This demonstrates that, although it tends to overestimate RU efficiency at low transmit power and underestimate it at higher transmit power (especially for *Ma-L18*), the model accurately reflects the general trend in power efficiency.

Next, Figure 5.14 compares the power consumption predicted by the BS power model with the corresponding validation data for typical BBU configurations. In this case, the model systematically overestimates the fully active power consumption, suggesting that further refinement of the proposed DBB power model would be beneficial in future works. This systematical bias can be explained by limitations in the empirical dataset used for model calibration. In particular, the DBB model was developed based on incomplete information, with technological parameters largely derived from technical documentation reporting only single “typical” power consumption values, rather than data points across multiple load levels. In addition, the validation set only includes BBUs manufactured by a different manufacturer than the ones used for model calibration. Consequently, part of the observed discrepancy may also reflect differences in energy performance across manufacturers, rather than a modeling bias alone.

Another potential source of variability in the validation set is the manufactur-

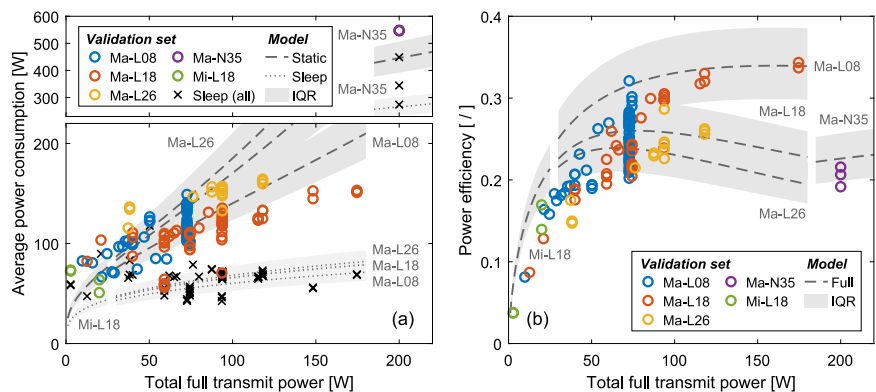


Fig. 5.13 Comparison of model predictions and validation data for typical radio unit configurations: (a) static and full sleep power consumption, and (b) power efficiency at full load. Although static power and power efficiency are sometimes overestimated, validation data generally falls within the inter-quartile range (IQR) of model predictions.

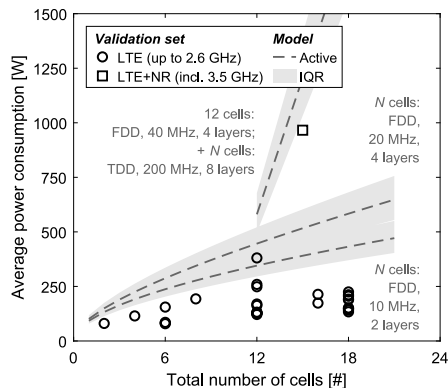


Fig. 5.14 Comparison of model predictions and validation data for fully active power consumption of multiple baseband unit configurations. Validation data mostly lie below the inter-quartile range (IQR) of model predictions, indicating a systematic overestimation.

ing year of the examined BS components. Accordingly, Figure 5.15 reports the manufacturing years of RUs and BBUs included in the validation set and categorized by typical configurations. This shows that most components were manufactured between 2017 and 2021, except for some older *Ma-L08* and *Ma-L18* RUs, as well as some BBUs. Since most components were manufactured during a relatively narrow period, a limited technological heterogeneity can be expected within the validation set, meaning comparable energy performance across similar components. As a result, differences in manufacturing years cannot fully explain the remain-

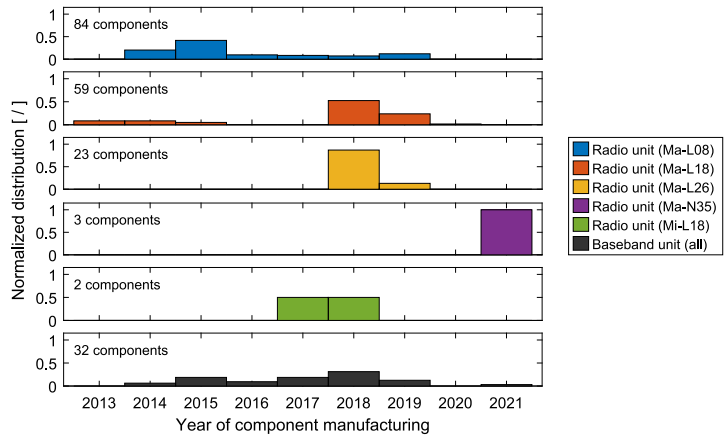


Fig. 5.15 Distribution of manufacturing years for the radio units and baseband units in the validation set, categorized by typical configurations. Most of these components were manufactured between 2017 and 2021, except for the older *Ma-L08* radio units.

ing discrepancies between the model predictions and the validation data. Further model improvements are therefore needed to achieve greater accuracy. Note that additional analyses of the validation set are provided in Appendix A.4.

5.8 Discussion

The power model developed in this chapter addresses the main research gaps identified in Chapter 3 regarding the assessment of BS energy consumption. Specifically, the proposed model builds upon existing bottom-up power models and incorporates top-down calibration using on-site measurements and technical documentation. This hybrid modeling approach thus strengthens the physical realism of the model. Unlike many existing models that focus on single-band BS configurations, the proposed power model targets multi-band BSs and provides a consistent representation of different BS components, including traditional RUs and modern AAUs, across various configurations. Moreover, explicitly modeling power consumption at multiple time scales ensures consistent analysis of fixed and dynamic PSSs, whose effects may depend on short-term activation strategies while targeting energy savings over longer time periods. Furthermore, the detailed analytical PA model accounts for signal waveform, PA architecture, and semiconductor technologies, extending beyond the simplified assumption of PA linearity commonly adopted in existing models. Together, these elements enable the proposed power model to consistently assess and compare the power consumption of commercial BS configurations under various operating conditions.

The results obtained in this chapter for typical BS configurations confirm a key conclusion from the literature: static power significantly contributes to BS power consumption, especially in microcell BSs. However, substantial differences emerge when these results are compared with those obtained from the flexible power models proposed by Debaillie et al. [170] and Desset et al. [173]. For typical macro BSs equipped with traditional RUs, the model developed in this chapter predicts +20-40% power consumption at full load and +40-60% power consumption at no load. The discrepancy is even more pronounced for BS configurations with AAUs, for which the proposed model predicts $\times 5$ -10 the power consumption estimated by previous flexible models. These discrepancies primarily stem from the more detailed representation of the AS and its constituent PAs in this chapter, as well as the higher static power consumption estimated for TRXs, particularly with massive-MIMO. Therefore, these findings raise concerns regarding the ability of these widely used power models to support the planning and optimization of real-world RAN deployments, as they may significantly underestimate the power consumption of commercial BS configurations.

Nevertheless, the proposed power model presents several limitations. First, although the estimation of technological model parameters relies on a relatively large empirical dataset, it mainly reflects commercial technologies from a few manufacturers. Thus, the model does not capture the full diversity of BS component designs across manufacturers. Second, the power consumption breakdown at the subcomponent level is generally inferred indirectly because measurements were not performed separately for individual subcomponents. As a result, the allocation of power consumption between subcomponents is more uncertain than the total power consumption assessed at the component level. Third, the proposed model does not cover emerging BS designs and configurations that could be deployed in the near or medium term (e.g., small-cell BSs, cloud-based baseband processing, or mmWave frequency bands), which would require dedicated refinements and extensions supported by additional empirical data. Finally, certain modeling assumptions that are appropriate for hourly energy assessments may limit the realism of short-term power modeling. In particular, assuming an even load distribution across active TRXs and PAs prevents the analysis of unbalanced component operation. Moreover, neglecting power overheads and transition delays between operating modes implies that rapid activations, deactivations, and associated power fluctuations are not accurately captured under dynamic PSSs. This simplification may therefore lead to an overestimation of achievable energy savings and hide potential PSS trade-offs.

Despite these limitations, the relatively low complexity of the proposed power model is a deliberate design choice intended to ensure usability, flexibility, and interpretability. These characteristics are particularly relevant for future research involving the evaluation of different BS configurations under various operating conditions. The technological parameter estimates are also intended to be updated

as new empirical data becomes available, without requiring a modification to the general model structure. For instance, future works could set custom parameter values to evaluate alternative communication protocols, PA architectures, or semiconductor technologies. This flexibility is important for reflecting the evolution of BS designs and PSSs. It also enables the exploration of BS configurations that extend beyond the initial scope of the model. Furthermore, users of the model are encouraged to perform uncertainty and sensitivity analyses based on the uncertainty quantification presented in this chapter. Although this aspect is largely overlooked in the literature, it is essential to prevent overinterpreting energy consumption results and marginal differences between configurations. Overall, the proposed BS power model establishes a realistic baseline and a structured assessment framework for future works targeting the technological development of BSs. These developments are especially important for achieving substantial energy savings during low- and no-load operations, including sleep modes and PSSs. Potential BS and PSS developments are further discussed in Chapter 7.

Summary

This chapter develops a parametric model of BS power consumption designed for use within the integrated RAN model. The BS is modeled by aggregating power models of its functional components, including the DBB, AFE, AS, ACS, and UPS. Each component is modeled for multiple operating modes at different time scales and usage levels, enabling the analysis of both fixed and dynamic PSSs. The BS usage is characterized by physical resource load rather than data traffic volume to ensure a robust site-independent modeling. Technological parameters are estimated using on-site measurements from MNOs and technical documentation from equipment manufacturers. A detailed analytical power model is also developed for PAs, showing that the PAPR of 4G-LTE and 5G-NR waveforms degrades the efficiency of conventional PA architectures. Applying the full power model to typical BS configurations shows that static power accounts for a large share of total power consumption. At full load, PAs dominates the power consumption of traditional BSs, while AFE becomes equally important with massive-MIMO. Unlike macrocell BSs, DBB dominates the power consumption of microcell BSs. At no load, power consumption can be reduced by up to 50% through sleep modes. A fully active macrocell BS consumes 0.5-1.5 kW per traditional band and 2-4 kW when using massive-MIMO. In contrast, a single-band microcell BS consumes around 0.2 kW. Model uncertainty is quantified as $\pm 10\%$, and model validation demonstrates a good prediction accuracy for RUs, though limitations remain for the DBB model.

6

Parametric model for life-cycle environmental impacts of base stations

This chapter develops a parametric model for assessing the environmental impacts of commercial BS architectures, specifically macro- and micro-cellular BSs that support one or more sub-6 GHz frequency bands in 4G-LTE or 5G-NR. Grounded in the LCA methodology, this model encompasses multiple impact indicators and includes all life-cycle stages. The production stage is the primary focus of this chapter, whereas the use stage is modeled using the BS power consumption model developed in Chapter 5. The proposed life-cycle model builds upon the state-of-the-art LCAs of BSs reviewed in Chapter 3 and seeks to address the associated research gaps. Moreover, this model is designed to be integrated within the parametric RAN model in order to contribute to addressing RQ1. Following the methodology introduced in Chapter 4, this chapter develops analytical life-cycle models for different BS components based on variables such as the bandwidth, BS lifetime, electricity supply source, etc. In addition, realistic technological parameter values and impact factors are estimated using specific empirical data sources. Overall, the proposed life-cycle environmental impact model enables quantitative assessments and consistent comparisons of various BS configurations.

This chapter begins with a refined goal and scope definition for the BS life-cycle model in Section 6.1, followed by its specific modeling approach in Section 6.2. Then, Section 6.3 develops an analytical model for the foreground system, and Section 6.4 calculates the corresponding impact factors for the background system. To ensure applicability of the model in real-world contexts, these two sections derive

the numerical estimates using regression analysis of empirical data and quantify the associated uncertainties. Next, Section 6.5 illustrates the practical use of the proposed life-cycle model by assessing five typical BS configurations. Finally, Section 6.6 validates the life-cycle model against independent observations, and Section 6.7 discusses the main contributions and limitations, as well as perspectives for future works. The content of this chapter is largely based on [JP3] and its supplementary material. This publication resulted from a collaboration with Robin Dethienne, who contributed to the conceptualization of the overall model and, in particular, to the analysis of the raw empirical data used to derive the environmental impact factors provided in Section 6.4.

6.1 Goal and scope

The specific goal and scope of the BS life-cycle environmental impact model complements the general goal and scope of the integrated RAN model defined in Section 4.1. Specifically, the BS life-cycle model applies the LCA methodology standardized by the ISO 14040:2006 [101] and ISO 14044:2006 [102]. In addition, this model is developed based on the ITU Recommendation L.1410 [188] for applying the LCA methodology to ICTs.

Within the integrated RAN model, the proposed BS life-cycle model assesses the total environmental impacts of the BS throughout its entire life cycle, from cradle to grave. This model is designed to study a wide range of BS configurations based on the set of model variables φ_{BS} defined in Section 4.3.3. Consistent with the RAN model boundaries, the life-cycle model includes the production, distribution, use and EoL stages of all communication-specific BS components. Conversely, it excludes support goods and support activities, core network components, data centers, and UEs. While the BS life-cycle model targets the assessment of multiple environmental impact categories (e.g., acidification, land use, ecotoxicity, etc.), this model primarily focuses on climate change through the GWP indicator. Three reasons justify this focus: (i) the Planetary Boundaries framework indicates that this impact category is of primary importance regarding the environmental sustainability challenge [41], (ii) LCIA methods are generally more robust for this category than for the other categories [73, 235], and (iii) this category aligns more directly with current engineering practices [57].

The environmental impacts assessed by the BS life-cycle model are obtained by conducting a parametric LCA in which the BS is the product system. In this LCA, the results are calculated for the 16 environmental impact categories of the LCIA method EF 3.1 without long-term effects [197]. The corresponding FU is defined as *the provision of given terrestrial wireless communication service(s) by one BS deployed in a given region*. This definition is intentionally generic and non-quantitative (as indicated by the term *given*) which provides flexibility to study various BS config-

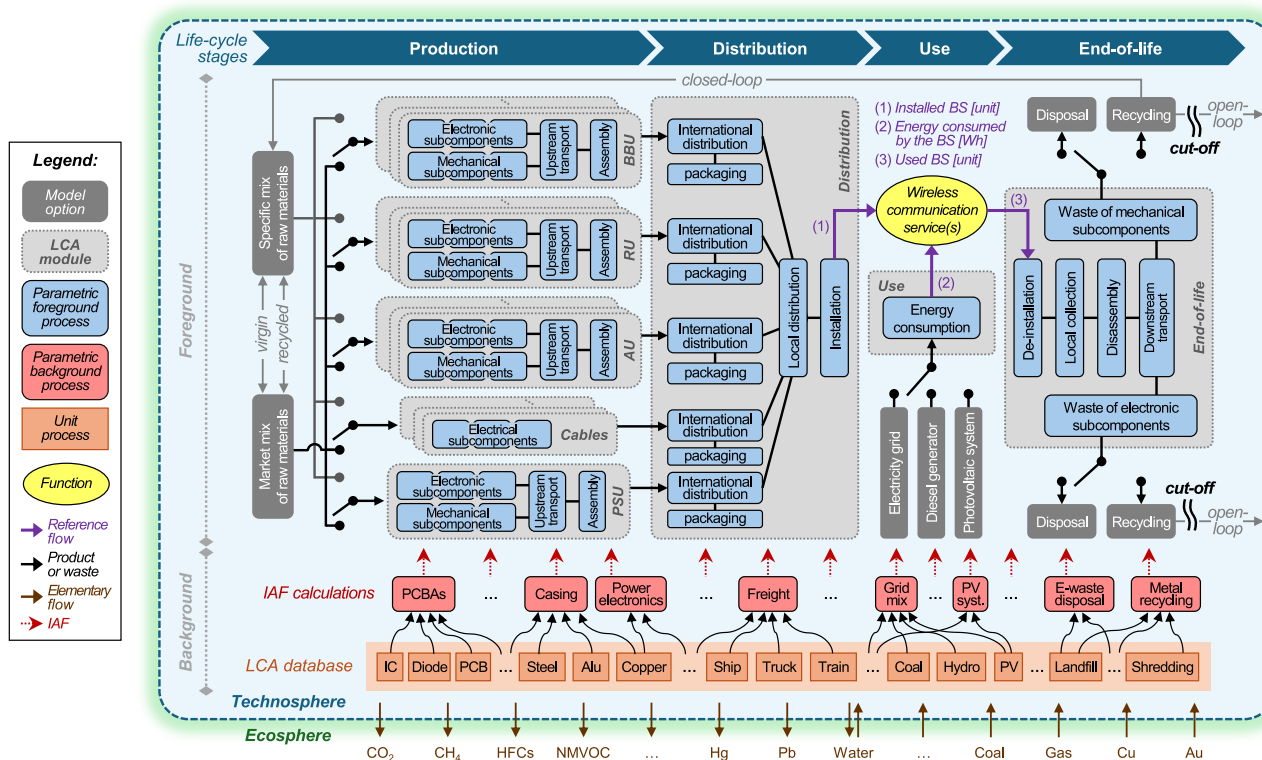


Fig. 6.1 Flow diagram of the life-cycle environmental impact model of a base station. The foreground system combines parametric foreground processes in several life cycle assessment (LCA) modules, which, in some cases, depend on specific model options. The background system builds parametric background processes based on unit processes from a database to calculate impact assessment factors (IAFs).

urations. However, the FU definition should be refined and quantified to meet the specific goal and scope of a particular LCA study. For instance, the provided communication service(s) should be specified for a quantified time period (e.g., 1 year), a quantified coverage (e.g., 1 km^2), a quantified unit of communication service (e.g., 1 GB of data traffic), a specific region (e.g., in Belgium), etc. Different BS configurations can also fulfill a specific quantified FU through differing configurations of reference flows. Figure 6.1 shows the flow diagram of the proposed BS life-cycle model, highlighting the FU and the three reference flows.

As shown in Figure 6.1, the life-cycle model combines a foreground and a background system [73]. The main processes of this model are the foreground processes for which parametric models are established. Background modeling of these processes then consists of combining generic unit processes from the LCI database “ecoinvent version 3.10” [236]. Adopting the attributional modeling framework, the BS life-cycle model relies on the “allocation, cut-off by classification” system model of ecoinvent (well known as “cut-off”). This conventional system model assigns the burden of waste treatment to systems that produce the waste, and the burden of recycling processes to systems that use the recyclable materials obtained burden-free from previous systems [236]. In general, no additional allocation procedure is required in the foreground system because the foreground processes deliver separate product flows. One exception relates to freight transportation impacts, which are allocated to based on transported mass and transport distance. Additionally, some specific FUs may require special allocation procedures, e.g., when the FU focuses on a specific band or a specific communication service.

In the BS life-cycle model, the allocation of burdens and credits between two successive product systems (which may provide different functions) follows the same approach as the “cut-off” system model [236], thereby ensuring consistency. Accordingly, no benefits from recycling are allocated to the system that ends with recyclable waste, and all impacts from the recycling process are attributed to the use of the recycled materials in the subsequent system. As depicted in Figure 6.1, the processes associated with open-loop recycling are cut off once subcomponent waste leaves the product system at the EoL. At the production stage, however, the use of recycled raw materials embeds the impacts of prior recycling processes. When closed-loop recycling is involved, the cut-off approach does not affect the total impacts of the BS life cycle. Rather, the impacts of closed-loop recycling processes are counted at the production stage instead of the EoL stage.

Since the QoS provided by a given BS configuration depends not only on the BS configuration variables but also on communication-related variables (e.g., the signal propagation environment, BS and UE densities, etc.), a communication performance model is needed to relate the BS life-cycle environmental impacts to its functional performance. Such a communication performance model is included in the integrated RAN model (see Section 4.3.1) but is not presented in this thesis. Combining these two BS models then enables relating the total environmental im-

pacts of the BS life cycle to the FU under study and deriving associated relative metrics, such as the carbon intensity per GB of data traffic, per user, per km² of coverage, or per MHz of occupied spectrum.

6.2 Modeling approach

The modeling approach for the BS life-cycle environmental impact model builds on the modeling approach for the integrated RAN model described in Section 4.2. Specifically, this model employs the physical representation of the BS architecture for model development, technological parameter estimation, and model validation.

6.2.1 Modeling strategies

The physical architecture representation of a large-cell (macro or micro) BS consists of six types of physical components (see Section 4.2.3). Five are classical types of components: the BBU, RU, AU, PSU, and external cables. The sixth type of component is the AAU, which is a special component that combines a RRU with an AU. The material composition of these components varies according to the BS configuration. However, conducting a LCA of such a complex and heterogeneous product system is known to be labor-intensive and time-consuming [237]. Therefore, two modeling strategies are used together to perform the LCA: the modular LCA strategy and the parametric LCA strategy [189]. This approach further allows for a detailed breakdown of impact results per BS component or life-cycle stage.

The modular LCA strategy involves modeling the product system around reusable elements called LCA modules. These LCA modules are first modeled separately, and then all modules are aggregated together to constitute the whole system [189]. The BS life-cycle model defines eight types of LCA modules: five representing the production of classical BS components (i.e., the BBU, RU, AU, PSU, and external cables) and three for modeling the distribution, use, and EoL stages (see Figure 6.1). The production of the special AAU component is split between the RU and AU production modules. In addition, the modules representing the production of the BBU, RU, AU and cables can be used multiple times for modeling the production of a single BS, i.e., once for each cell¹.

Since the LCIA method covers multiple impact indicators, the total environmental impacts of the BS are represented by the column vector $\mathbf{I}_{BS}$ (whose elements correspond to the different impact categories), which is calculated as

$$\mathbf{I}_{BS} = \sum_{m=1}^M \mathbf{I}_m, \quad (6.1)$$

where M is the total number of modules in the BS life-cycle model, and $\mathbf{I}_m$ is the

¹In this thesis, a *cell* is defined as one frequency band in one sector of one BS.

impact vector of the m th module. Since certain types of LCA modules can be reused multiple times in the model, $M \geq 8$.

The parametric LCA strategy aims to model the product system through a set of product-related parameters. This requires determining the functions linking these parameters to the environmental impacts of the system, which often involves regression analysis [189]. In the BS life-cycle model, the LCA modules consist of one or more foreground processes (see Figure 6.1). For a given impact category, the environmental impact of a foreground process is the product of two terms: the quantity of that process and its corresponding environmental impact factor. Adopting the parametric LCA strategy, these two terms are modeled by parametric (often nonlinear) functions of φ , which denotes the subset of BS configuration variables φ_{BS} that specifically affects the environmental impact model (see Section 4.3.3), such that $\varphi \subseteq \varphi_{BS}$. For instance, φ includes the bandwidth B , the carrier frequency f , the number of TRXs N_{TRX} , etc.

The total environmental impacts of a LCA module m are then computed by adding the impacts of all its K_m foreground processes. Thus, the column vector of the total impacts of this module across all impact categories is calculated as

$$\mathbf{I}_m(\varphi) = \sum_{k=1}^{K_m} Q_{m,k}(\varphi) \mathbf{F}_{m,k}(\varphi), \quad (6.2)$$

where $Q_{m,k}(\varphi)$ is the parametric quantity of the foreground process k in the module, and $\mathbf{F}_{m,k}(\varphi)$ is the column vector of corresponding parametric impact factors. Equation (6.2) can then be rewritten as a matrix product as

$$\mathbf{I}_m(\varphi) = \mathbb{F}_m(\varphi) \mathbf{Q}_m(\varphi)^T, \quad (6.3)$$

where $\mathbf{Q}_m(\varphi)$ is the row vector containing all the K_m parametric foreground process quantities of module m , and $\mathbb{F}_m(\varphi)$ is the matrix resulting from horizontal concatenation of column vectors $\mathbf{F}_{m,k}(\varphi)$. Note that the units of the elements of the vector $\mathbf{Q}_m(\varphi)$ may differ because each element scales impact factors calculated for a specific reference flow (e.g., 1 kg, 1 km, 1 cm², etc.).

6.2.2 Model structure

The structure of the life-cycle BS model combines the modular and parametric LCA strategies to compute $\mathbf{I}_{BS}$. In this model, the total environmental impacts of producing the BBU, RU, AU and external cables for one cell c are represented by $\mathbf{I}_{BBU,c}$, $\mathbf{I}_{RU,c}$, $\mathbf{I}_{AU,c}$ and $\mathbf{I}_{cab,c}$ respectively. These impacts depend on the specific configuration of the associated cell. In addition, the impacts of producing the PSU serving all cells of the BS are represented by $\mathbf{I}_{PSU}$, and the impacts of the distribution, use and EoL stages are represented by $\mathbf{I}_{dist}$, $\mathbf{I}_{use}$ and $\mathbf{I}_{EoL}$, respectively. The total envi-

ronmental impacts of the BS are then calculated as

$$\mathbf{I}_{BS} = \sum_{c=1}^{N_C} (\mathbf{I}_{BBU,c} + \mathbf{I}_{RU,c} + \mathbf{I}_{AU,c} + \mathbf{I}_{cab,c}) + \mathbf{I}_{PSU} + \mathbf{I}_{dist} + \mathbf{I}_{use} + \mathbf{I}_{EoL}, \quad (6.4)$$

where N_C is the total number of cells in the BS, calculated as $N_C = N_B N_S$. All terms in Equation (6.4) can be expressed individually using Equation (6.3).

Therefore, the foreground process inventory (FPI) aims to model the full set of parametric foreground process quantities for the entire BS, denoted by $\mathbf{Q}_{BS}(\varphi)$. By denoting the corresponding matrix of impact assessment factors (IAFs) for the entire BS by $\mathbf{F}_{BS}(\varphi)$ then yields

$$\mathbf{I}_{BS}(\varphi) = \mathbf{F}_{BS}(\varphi) \mathbf{Q}_{BS}(\varphi)^T. \quad (6.5)$$

This distinction between the FPI quantities and the IAFs aims to bring transparency and flexibility to the model, especially for model users who prefer to use their own IAFs, e.g., for alternative technologies, alternative operating locations, based on impact factors from another database, etc. Therefore, the FPI modeling and the IAF calculations are addressed separately in Section 6.3 and Section 6.4.

6.3 Foreground process inventory

The FPI involves defining the parametric functions of the foreground process quantities that constitute the vector $\mathbf{Q}_m(\varphi)$ for each LCA module of the BS life-cycle model. The complete set of parametric foreground processes included in the model is listed in Table 6.1, along with the scaling units to be used when multiplying them by the IAFs. To model a complete BS, the modules representing the production of the BBU, RU, AU and cables must be replicated for each BS cell. The rest of this section is structured in two parts. First, it introduces the analytical representation of the parametric models for all foreground processes of the LCA modules. Second, it provides numerical estimates of the associated technological parameters and quantifies the corresponding uncertainty.

6.3.1 Production stage

The production stage includes the raw material acquisition, manufacturing, transport and assembly of BS components. As shown in Figure 6.1, raw materials can be either virgin or recycled. By default, the life-cycle model assumes that the weighting between these two sources corresponds to the *market mix* for each material. Another option allows for the use of a *specific raw material mix* containing more recycled material than the market average. For consistency, this option is conditional

Table 6.1 Complete set of parametric foreground processes in the life-cycle model

Scope ^a	Description	Symbol	Unit
<i>Baseband unit production</i>			
Cell	Production of the data link layer boards	$\mathcal{E}_{link}$	cm ²
Cell	Production of the physical layer boards	$\mathcal{E}_{phy}$	cm ²
Cell	Production of the ancillary subcomponents	$\mathcal{E}_{anci}$	cm ²
Cell	Production of the mechanical subcomponents	$\mathcal{M}_{BBU}$	kg
Cell	Upstream transport of the baseband unit subcomponents	$\mathcal{T}_{BBU}$	kg·km
Cell	Final assembly of the baseband unit	$\mathcal{A}_{BBU}$	Wh
<i>Radio unit production</i>			
Cell	Production of the processing units	$\mathcal{E}_{proc}$	cm ²
Cell	Production of the transceivers	$\mathcal{E}_{TRX}$	cm ²
Cell	Production of the power amplifiers	$\mathcal{E}_{PA}$	cm ²
Cell	Production of the power management and supply units	$\mathcal{E}_{sup}$	cm ²
Cell	Production of the mechanical subcomponents	$\mathcal{M}_{RU}$	kg
Cell	Upstream transport of the radio unit subcomponents	$\mathcal{T}_{RU}$	kg·km
Cell	Final assembly of the radio unit	$\mathcal{A}_{RU}$	Wh
<i>Antenna unit production</i>			
Cell	Production of the antenna elements	$\mathcal{E}_{AU}$	kg
Cell	Production of the mechanical subcomponents	$\mathcal{M}_{AU}$	kg
Cell	Upstream transport of the antenna unit subcomponents	$\mathcal{T}_{AU}$	kg·km
Cell	Final assembly of the antenna unit	$\mathcal{A}_{AU}$	Wh
<i>Power supply unit production</i>			
BS	Production of the power converters	$\mathcal{E}_{conv}$	kg
BS	Production of the backup batteries	$\mathcal{E}_{batt}$	kg
BS	Production of the mechanical subcomponents	$\mathcal{M}_{PSU}$	kg
BS	Upstream transport of the power supply unit subcomponents	$\mathcal{T}_{PSU}$	kg·km
BS	Final assembly of the power supply unit	$\mathcal{A}_{PSU}$	Wh
<i>External cable production</i>			
Cell	Production of the optical fiber cables	$\mathcal{E}_{opt}$	m
Cell	Production of the coaxial cables	$\mathcal{E}_{coax}$	m
Cell	Production of the power cables	$\mathcal{E}_{pwr}$	m
<i>Distribution stage</i>			
BS	Production and disposal of the packaging	$\mathcal{M}_{pack}$	kg
BS	International distribution of the base station components	$\mathcal{T}_{inter}$	kg·km
BS	Local distribution of the base station	$\mathcal{T}_{loc}$	km
BS	Installation of the base station	$\mathcal{A}_{inst}$	Wh
<i>Use stage</i>			
BS	Energy consumption of the base station	$\mathcal{E}_{use}$	Wh
<i>End-of-life stage</i>			
BS	Waste management of the electronic subcomponents	$\mathcal{E}_{waste}$	kg
BS	Waste management of the mechanical subcomponents	$\mathcal{M}_{waste}$	kg
BS	Local collection of the base station	$\mathcal{T}_{col}$	km
BS	Downstream transport of waste from the base station	$\mathcal{T}_{down}$	kg·km
BS	Deinstallation of the base station	$\mathcal{A}_{deinst}$	Wh
BS	Disassembly of the base station components	$\mathcal{A}_{disas}$	Wh

^a "BS" processes are for the entire base station, and "Cell" processes are for each cell.

upon the adoption of recycling at the EoL. Moreover, specific raw material mixes are limited to materials that can be recycled in a closed loop within the product system, i.e., the metals in mechanical structures but not the materials in electronic components, as they require a very high level of purity [238].

The foreground processes involved in BS component production are grouped into four types: (i) the production of electronic subcomponents, (ii) the production of mechanical subcomponents, (iii) the upstream transport of subcomponents from their respective manufacturing factories to the final assembly factory, and (iv) the final assembly of the component. Denoting $\mathcal{E}_m(\varphi)$, $\mathcal{M}_m(\varphi)$, $\mathcal{T}_m(\varphi)$ and $\mathcal{A}_m(\varphi)$ the row vectors of parametric process quantities for each of these four process types in module m , the vector $\mathbf{Q}_m(\varphi)$ becomes their horizontal concatenation as

$$\mathbf{Q}_m(\varphi) = \begin{bmatrix} \mathcal{E}_m(\varphi) & \mathcal{M}_m(\varphi) & \mathcal{T}_m(\varphi) & \mathcal{A}_m(\varphi) \end{bmatrix}. \quad (6.6)$$

In Table 6.1, these four types of process are distinguished by a specific symbol, respectively $\mathcal{E}$, $\mathcal{M}$, $\mathcal{T}$ and $\mathcal{A}$. The following sections describe the parametric functions of these four types of component production processes. Note that the same symbols are also used in the other life-cycle stages to identify related processes: $\mathcal{T}$ for transport, $\mathcal{A}$ for (de)installation and disassembly, and $\mathcal{E}$ and $\mathcal{M}$ for waste management of electronic and mechanical subcomponents.

Production of electronic and mechanical subcomponents The production of most subcomponents is modeled by scaling their quantity with respect to a reference situation using scaling variables, similar to the approach in [169, 170, 173] for BS power models. Formally, the quantity $Q_k(\varphi)$ of process k in a configuration described by φ is obtained by scaling the reference quantity Q_k^{ref} across S scaling variables as

$$Q_k(\varphi) = Q_k^{ref} \prod_{s=1}^S \left(\frac{\varphi_s}{\varphi_s^*} \right)^{\alpha_{k,s}}, \quad (6.7)$$

where the scaling variable s has an actual value φ_s , a reference value φ_s^* , and a process-specific scaling exponent $\alpha_{k,s}$. The model-agnostic reference situation for the scaling variables is defined by the reference frequency $f^* = 1$ GHz, reference bandwidth $B^* = 1$ MHz, reference power $P^* = 1$ W, reference duration $T^* = 1$ hour, reference mass $M^* = 1$ kg, and reference surface area $A^* = 1$ cm². In this model, the reference quantity Q_k^{ref} and the set of $\alpha_{k,s}$ are the technological parameters.

Upstream transport The modeling approach for the upstream transport is the same for all BS components. Upstream transport consists of a mix of freight transportation means, expressed as the product of transported mass and transport distance (in kg·km). For a given BS component, the total upstream transport quantity is modeled by multiplying the total mass of its $\tilde{K}_m$ electronic and mechanical sub-

components by the upstream transport distance d_m^{up} as

$$\mathcal{T}_m(\varphi) = d_m^{up} \sum_{k=1}^{\tilde{K}_m} Q_{m,k}(\varphi) \rho_k, \quad (6.8)$$

where $Q_{m,k}(\varphi)$ is the quantity of subcomponent k in production stage module m , and ρ_k is the mass density of subcomponent k if its quantity is not expressed as its mass (otherwise $\rho_k = 1 \text{ kg/kg}$). The packaging is not modeled for upstream transport because its impacts are considered negligible.

Final assembly The modeling approach for the final assembly is also the same for all BS components. Final assembly of BS components is simply modeled by the electricity used for assembling subcomponents into final components. Other types of assembly processes, as well as the construction of the assembly factory, are neglected due to a lack of information. Moreover, manufacturer support activities are outside the scope of the network model (see Section 4.1).

6.3.1.1 Baseband unit production

The BBU performs the digital functions of the BS and comprises a set of boards that handle the data link and physical layers of communication protocols.

Production of electronic subcomponents The BBU boards are the electronic subcomponents whose production is modeled by the surface area of their printed circuit board assembly (PCBA), respectively denoted by $\mathcal{E}_{link}$ and $\mathcal{E}_{phy}$. The total PCBA area of data link layer boards for the entire BS scales with the total number of cells N_C . Since BBU production is expressed per cell in Equation (6.4), an equal fraction of their total PCBA area is allocated to each cell as

$$\mathcal{E}_{link} = \frac{1}{N_C} \mathcal{E}_{link}^{ref} \cdot (N_C)^{\alpha_{link}}, \quad (6.9)$$

where $\mathcal{E}_{link}^{ref}$ and α_{link} are technological parameters.

For a given cell, the PCBA area of physical layer boards is modeled per spatial data layer² whose associated area scales with the layer capacity reflected by the bandwidth B . Denoting the number of spatial layers in the cell by N_L , this yields

$$\mathcal{E}_{phy} = N_{BBP} N_L \mathcal{E}_{phy}^{ref} \cdot \left(\frac{B}{B^*} \right)^{\alpha_{phy}}, \quad (6.10)$$

where $\mathcal{E}_{phy}^{ref}$ and α_{phy} are technological parameters, and N_{BBP} models the number of baseband processing units required for duplexing the DL and UL. The latter varies

²In this thesis, a *spatial data layer* is defined as a physical channel able to convey up to one independent data stream. The fixed number of spatial data layers corresponds to the maximum number of data streams that can be spatially multiplexed within a cell.

with the duplex scheme because DL and UL operate simultaneously in FDD, but sequentially in TDD. This suggests that a single processing unit could potentially support both the DL and UL in TDD, while two separate units are likely needed in FDD. The N_{BBP} factor is modeled as

$$N_{BBP} = (\tau_{DL} + \tau_{UL}) + (2 - (\tau_{DL} - \tau_{UL})) \cdot \delta_{BBP}, \quad (6.11)$$

where τ_{DL} and τ_{UL} are respectively the DL and UL time ratios ($\tau_{DL} = \tau_{UL} = 1$ in FDD and $\tau_{DL} + \tau_{UL} = 1$ in TDD), and $\delta_{BBP} \in [0, 1]$ is a technological parameter modeling the degree of differentiation between DL and UL processing units.

An additional PCBA area models the production of ancillary subcomponents responsible for power management, fan cooling, etc. This area is proportional to the sum of PCBA areas of the data link and physical layer boards as

$$\mathcal{E}_{anci} = (\mathcal{E}_{link} + \mathcal{E}_{phy}) \cdot \beta_{anci}, \quad (6.12)$$

where β_{anci} is the scaling factor which is a technological parameter.

Production of mechanical subcomponents The mechanical structure of the BBU includes the mechanical parts of its boards (e.g., front panel, screws, etc.) plus the subrack that holds them together. The production of these mechanical subcomponents for one BS cell is modeled by their total mass, which scales with the total PCBA area for the cell as

$$\mathcal{M}_{BBU} = \mathcal{M}_{BBU}^{ref} \cdot \left(\frac{\mathcal{E}_{link} + \mathcal{E}_{phy} + \mathcal{E}_{anci}}{A^*} \right)^{\alpha_{BBU}}, \quad (6.13)$$

where $\mathcal{M}_{BBU}^{ref}$ and α_{BBU} are technological parameters.

Upstream transport The upstream transport for BBU production is modeled as

$$\mathcal{T}_{BBU} = d_{BBU}^{up} \cdot \left((\mathcal{E}_{link} + \mathcal{E}_{phy} + \mathcal{E}_{anci}) \cdot \rho_{PCBA} + \mathcal{M}_{BBU} \right), \quad (6.14)$$

where d_{BBU}^{up} is the upstream transport distance of BBU subcomponents, and ρ_{PCBA} is the PCBA mass density (in kg/cm^2), representing two technological parameters.

Final assembly The final assembly of the BBU is modeled by a fixed amount of electricity consumption per cell, represented by $\mathcal{A}_{BBU}$. Thus, the total electricity consumption for assembling the complete BBU of the BS scales linearly with N_C .

As a result, the complete row vector of foreground process quantities for the BBU production module is

$$\mathbf{Q}_{BBU} = [\mathcal{E}_{link} \quad \mathcal{E}_{phy} \quad \mathcal{E}_{anci} \quad \mathcal{M}_{BBU} \quad \mathcal{T}_{BBU} \quad \mathcal{A}_{BBU}]. \quad (6.15)$$

6.3.1.2 Radio unit production

A RU contains the AFE and the PAs for one BS cell. The AFE performs analog TX and RX functions, as well as digital-to-analog and analog-to-digital conversion. Then, the PAs amplify the RF signals before they are emitted by the antennas. Regarding AAUs, the RU production module covers the production of active electronic subcomponents, as well as the mechanical structure, casing and heat sinks. On the other hand, the production of the antenna part of AAUs, including the radome and AEs, is modeled separately in the AU production module.

Production of electronic subcomponents Functions of RUs are performed by three types of electronic subcomponents: processing units, TRXs and PAs. As for the BBU, the production of these subcomponents is modeled by the surface area of their PCBA, respectively denoted by $\mathcal{E}_{proc}$, $2\mathcal{E}_{TRX}$ and $\mathcal{E}_{PA}$. The factor 2 in front of $\mathcal{E}_{TRX}$ indicates that a TRX includes a pair of TX and RX chains, whereas the PA is only used for TX. The PCBA area of each subcomponent is modeled to scale with the maximum transmit power per chain P_{TX}^{max} , which is assumed to be a proxy for their complexity and hence their size. Next, the scaled PCBA areas are multiplied by N_{TRX} , the total number of TRXs in the RU, yielding

$$\mathcal{E}_{proc} = N_{TRX} \mathcal{E}_{proc}^{ref} \cdot \left(\frac{P_{TX}^{max}}{P^*} \right)^{\alpha_{proc}}, \quad (6.16)$$

$$\mathcal{E}_{TRX} = 2N_{TRX} \mathcal{E}_{TRX}^{ref} \cdot \left(\frac{P_{TX}^{max}}{P^*} \right)^{\alpha_{TRX}}, \quad (6.17)$$

and

$$\mathcal{E}_{PA} = N_{TRX} \mathcal{E}_{PA}^{ref} \cdot \left(\frac{P_{TX}^{max}}{P^*} \right)^{\alpha_{PA}}, \quad (6.18)$$

where $\mathcal{E}_{proc}^{ref}$, $\mathcal{E}_{TRX}^{ref}$, $\mathcal{E}_{PA}^{ref}$, α_{proc} , α_{TRX} and α_{PA} are technological parameters.

An additional PCBA area is dedicated to the power management and supply within the RU. As observed in empirical data, the surface area of this subcomponent varies slightly across different RU configurations. This observation is explained by the same standard -48 V voltage that supplies all BS and hence RU components [196]. Therefore, the production of this power supply subcomponent is modeled as a constant PCBA area regardless of RU configuration as

$$\mathcal{E}_{sup} = \mathcal{E}_{sup}^{ref}, \quad (6.19)$$

where $\mathcal{E}_{sup}^{ref}$ is a technological parameter.

Production of mechanical subcomponents The mechanical structure of the RU combines a casing with heat sinks to ensure effective heat dissipation. It also supports the cavity filters which are commonly used in RUs for their ability to handle high amounts of power with low losses [239]. The production of these mechanical

subcomponents is modeled by their total mass, which scales with the total PCBA area in the RU as

$$\mathcal{M}_{RU} = \mathcal{M}_{RU}^{ref} \cdot \left(\frac{\mathcal{E}_{proc} + \mathcal{E}_{TRX} + \mathcal{E}_{PA} + \mathcal{E}_{sup}}{A^*} \right)^{\alpha_{RU}}, \quad (6.20)$$

where $\mathcal{M}_{BBU}^{ref}$ and α_{BBU} are technological parameters.

Upstream transport The upstream transport for RU production is modeled as

$$\mathcal{T}_{RU} = d_{RU}^{up} \cdot \left((\mathcal{E}_{proc} + \mathcal{E}_{TRX} + \mathcal{E}_{PA} + \mathcal{E}_{sup}) \cdot \rho_{PCBA} + \mathcal{M}_{RU} \right), \quad (6.21)$$

where d_{RU}^{up} is the upstream transport distance of RU subcomponents, and ρ_{PCBA} is the PCBA mass density (in kg/cm²), representing two technological parameters.

Final assembly The final assembly of the RU is modeled by a fixed amount of electricity consumption per RU, represented by $\mathcal{A}_{RU}$.

As a result, the complete row vector of foreground process quantities for the RU production module is

$$\mathbf{Q}_{RU} = [\mathcal{E}_{proc} \quad \mathcal{E}_{TRX} \quad \mathcal{E}_{PA} \quad \mathcal{E}_{sup} \quad \mathcal{M}_{RU} \quad \mathcal{T}_{RU} \quad \mathcal{A}_{RU}]. \quad (6.22)$$

In principle, combining multiple frequency bands into a single platform to form a multi-band RU could reduce the required quantity of electronic and mechanical subcomponents through mutualization. However, empirical data reveals no significant difference in material quantities allocated per band between single-band RUs and the corresponding multi-band RUs. Therefore, the per-cell modeling approach is assumed to be applicable to both single- and multi-band RUs. In practice, the use of multi-band RUs appears to be primarily motivated by cost-cutting considerations and by easier and faster on-site installation and dismantling by MNOs.

6.3.1.3 Antenna unit production

In an AU, each antenna array is associated with a specific frequency band. A single antenna array contains multiple AEs arranged in rows and columns and split into several subarrays. A subarray groups together multiple AEs and transmits and receives specific RF signals from and to TRXs to achieve MIMO and, when implemented, ABF [194, 195]. Moreover, the size of AEs is proportional to the wavelength of RF signals they emit, given by

$$\lambda = 30 \frac{f^*}{f}, \quad (6.23)$$

which is expressed in centimeters as f^* is in gigahertz. The size and number of AEs affect the models of both the electronic and mechanical subcomponent production.

Production of electronic subcomponents The electronic subcomponents of AUs are the AEs consisting of radiating elements, internal cables, and delay lines that control RF signal delay. The total number of AEs in one antenna array of the AU is denoted by N_{AE} . The mass of one AE is assumed to scale with its size, which is proportional to λ and hence scales with $1/f$. The production of electronic subcomponents of the AU for one cell is then modeled by the total mass of all AEs in the associated antenna array as

$$\mathcal{E}_{AU} = N_{AE} \mathcal{E}_{AU}^{ref} \cdot \left(\frac{f}{f^*} \right)^{-1}, \quad (6.24)$$

where $\mathcal{E}_{AU}^{ref}$ is a technological parameter.

Calculating N_{AE} involves the following considerations. First, the total number of AEs in the antenna array is $N_{AE} = N_{SA} N_{AE}^{SA}$, where N_{AE}^{SA} is the number of AEs per subarray. Second, the number of subarrays in an antenna array is $N_{SA} = N_{TRX}/N_{pol}$, where N_{TRX} is the number of TRXs in the associated RU, and N_{pol} denotes the number of polarizations. Indeed, each TRX handles one specific stream of RF signal for one polarization. When $N_{pol} = 2$, the subarray consists of cross-polarized AEs that support two signal streams at $\pm 45^\circ$, both connected to a dedicated TRX. Third, the maximum total antenna gain G_{TX}^{max} (in dBi) can be decomposed into a log-scale sum of the AE gain G_{AE} (in dBi), the subarray gain G_{SA} (in dB), and the maximum inter-subarray beamforming gain G_{BF}^{max} (in dB), as

$$G_{TX}^{max} = G_{AE} + G_{SA} + G_{BF}^{max}. \quad (6.25)$$

In the integrated RAN model, G_{TX}^{max} is a BS configuration variable.

Without ABF, subarrays are simply vertical linear arrays of AEs, and there is no signal combination between the different subarrays, yielding $G_{BF}^{max} = 0$. In this case, the subarray gain can be approximated by $G_{SA} = 10 \log_{10}(N_{AE}^{SA})$. With ABF, all AEs of the antenna array, can be used for ABF, including those from different subarrays, yielding $G_{SA} + G_{BF}^{max} \approx 10 \log_{10}(N_{AE})$. The resulting number of AEs in the entire antenna array, both without and with ABF, is

$$N_{AE} = \begin{cases} \frac{N_{TRX}}{N_{pol}} 10^{\left(\frac{G_{TX}^{max} - G_{AE}}{10} \right)} & \text{if } \kappa_{ABF} = \text{without} \\ 10^{\left(\frac{G_{TX}^{max} - G_{AE}}{10} \right)} & \text{if } \kappa_{ABF} = \text{with} \end{cases}, \quad (6.26)$$

where κ_{ABF} is a BS configuration variable that determines the ABF capabilities of the AU, and G_{AE} is a technological parameter that may differ for each case.

Production of mechanical subcomponents The mechanical structure of the AU consists of a reflective plane which focuses the radiation pattern of the antenna and supports the AEs, plus a radome to protect AEs from outdoor conditions. The size of this structure scales with the surface area of its constituent antenna arrays. The area of one single antenna array is calculated by multiplying its number of AEs with the occupied area per AE as

$$A_{array} = N_{AE} \beta_h \beta_v \lambda^2, \quad (6.27)$$

which is expressed in square-centimeters, as λ is expressed in centimeters in Equation (6.23), and where β_v and β_h are respectively the vertical and horizontal spacings between AEs, expressed in wavelength multipliers.

In general, arrays of frequency bands from different ranges (as defined in [240], e.g., 0.8 and 1.8 GHz) can be superimposed to save space and reduce wind load without interfering with each other. On the other hand, bands within the same frequency range (e.g., 1.8 and 2.1 GHz) cannot be superimposed because they may interfere with each other [194]. Thus, the total antenna area of an entire AU corresponds to the greatest area occupied by one frequency range as

$$A_{AU} = \max_j \left(\sum_{i=1}^{N_{B,j}} A_{array,i} \right), \quad (6.28)$$

where $A_{array,i}$ is the area occupied by the antenna array of frequency band i , calculated as in Equation (6.27), and $N_{B,j}$ is the number of frequency bands in frequency range j . The total mass of the mechanical structure of an entire AU is then assumed to scale with A_{AU} . Since AU production is expressed per cell in Equation (6.4), the total AU structure mass is uniformly allocated per supported band as

$$\mathcal{M}_{AU} = \frac{1}{N_B} \mathcal{M}_{AU}^{ref} \cdot \left(\frac{A_{AU}}{A^*} \right)^{\alpha_{AU}}, \quad (6.29)$$

where $\mathcal{M}_{AU}^{ref}$ and α_{AU} are technological parameters.

The general case applies directly to traditional passive AUs that are physically separated from RUs and host one or more antenna arrays. A special case arises with AAUs, which support only one frequency band. In this case, no mass allocation is necessary for modeling AU production, and Equation (6.29) simplifies to

$$\mathcal{M}_{AU} = \mathcal{M}_{AU}^{ref} \cdot \left(\frac{A_{array}}{A^*} \right)^{\alpha_{AU}}. \quad (6.30)$$

Since the AU structure is shared with the contiguous RU in AAUs, the AU production module only includes the radome. The reflective plane and the rest of the mechanical structure are assumed to be modeled by the RU production module.

In the life-cycle model, the mechanical AU structure of the N_B^{tradi} bands using traditional AUs is first modeled for each BS sector and then allocated per cell. In contrast, the mechanical AU structure of bands using AAUs is modeled independently for each cell. The total antenna area of the traditional AU, denoted by A_{AU}^{tradi} , is calculated by Equation (6.28), and the antenna area of the single band supported by an AAU, denoted by A_{array}^{AAU} , is calculated directly by Equation (6.27). Then, the mass of the mechanical structure for the AU in a given cell is

$$\mathcal{M}_{AU} = \begin{cases} \frac{1}{N_B^{tradi}} \mathcal{M}_{AU}^{ref} \cdot \left(\frac{A_{AU}^{tradi}}{A^*} \right)^{\alpha_{AU}} & \text{if } \kappa_{RU} \in \{\text{RFU}, \text{RRU}\} \\ \mathcal{M}_{AU}^{ref} \cdot \left(\frac{A_{array}^{AAU}}{A^*} \right)^{\alpha_{AU}} & \text{if } \kappa_{RU} = \text{AAU} \end{cases}, \quad (6.31)$$

where κ_{RU} is a BS configuration variable that determines the RU type per band and, subsequently, the type of the corresponding AU. Since an AAU combines an RU with an AU, $\mathcal{M}_{AU}^{ref}$ may differ between traditional AUs and AAUs.

Upstream transport The upstream transport for AU production is modeled as

$$\mathcal{T}_{AU} = d_{AU}^{up} \cdot (\mathcal{E}_{AU} + \mathcal{M}_{AU}), \quad (6.32)$$

where d_{AU}^{up} is a technological parameter representing the upstream transport distance of AU subcomponents.

Final assembly The final assembly of the AU is modeled by a fixed amount of electricity consumption per band, represented by $\mathcal{A}_{AU}$. Thus, the total electricity consumption for assembling an entire AU scales linearly with its number of bands.

As a result, the complete row vector of foreground process quantities for the AU production module is

$$\mathbf{Q}_{AU} = [\mathcal{E}_{AU} \quad \mathcal{M}_{AU} \quad \mathcal{T}_{AU} \quad \mathcal{A}_{AU}]. \quad (6.33)$$

6.3.1.4 Power supply unit production

The PSU supplies power to the BBU and all RUs of the BS. The size of the PSU primarily depends on the maximum power supply required by the entire BS as

$$P_{supply} = \max_x (P_{BS}(x)) = P_{BS}(1), \quad (6.34)$$

where $P_{BS}(x)$ is the total power consumption of the BS as a function of the physical resource load x . Typically, the maximum BS power consumption occurs at full physical load, i.e., when $x = 1$. Chapter 5 explains how to model $P_{BS}(x)$.

Production of electronic subcomponents Two types of electronic subcomponents are considered for the PSU: power converters and backup batteries. Their production is modeled by their mass, respectively denoted by $\mathcal{E}_{conv}$ and $\mathcal{E}_{batt}$. Power converters includes rectifiers, a power distribution panel, a controller, and fans for active cooling. Their total mass is assumed to scale with P_{supply} as

$$\mathcal{E}_{conv} = \mathcal{E}_{conv}^{ref} \cdot \left(\frac{P_{supply}}{P^*} \cdot (1 + \beta_{margin}) \right)^{\alpha_{conv}}, \quad (6.35)$$

where $\mathcal{E}_{conv}^{ref}$ and α_{conv} are two technological parameters, and β_{margin} is an additional parameter representing a power supply margin to account for PSU losses and other system robustness considerations.

The PSU may also include backup batteries to guarantee a reliable service in case of a power supply failure [193]. The mass of backup batteries is modeled to scale with the intended energy storage $E_{backup} = P_{supply} T_{backup}$ as

$$\mathcal{E}_{batt} = \mathcal{E}_{batt}^{ref} \cdot \left(\frac{P_{supply}}{P^*} \cdot \frac{T_{backup}}{T^*} \right)^{\alpha_{batt}}, \quad (6.36)$$

where T_{backup} is the backup duration at full BS load, and $\mathcal{E}_{batt}^{ref}$ and α_{batt} are two technological parameters. Since the BS does not operate at full load continuously, the actual backup duration may be longer than T_{backup} . Furthermore, the BS is expected to go into safety mode in case of supply failure, reducing its power consumption by deactivating some of its bands in order to guarantee a basic service. This allows the backup batteries to last even longer.

Production of mechanical subcomponents The mechanical structure of the PSU consists of the complete structure and casing of the BS cabinet, plus the subrack that houses electronic subcomponents of the PSU. The production of these mechanical subcomponents is modeled by their total mass, which scales with the total mass of electronic subcomponents as

$$\mathcal{M}_{PSU} = \mathcal{M}_{PSU}^{ref} \cdot \left(\frac{\mathcal{E}_{conv} + \mathcal{E}_{batt}}{M^*} \right)^{\alpha_{PSU}}, \quad (6.37)$$

where $\mathcal{M}_{PSU}^{ref}$ and α_{PSU} are technological parameters.

Upstream transport The upstream transport for PSU production is modeled as

$$\mathcal{T}_{PSU} = d_{PSU}^{up} \cdot (\mathcal{E}_{conv} + \mathcal{E}_{batt} + \mathcal{M}_{PSU}), \quad (6.38)$$

where d_{PSU}^{up} is a technological parameter representing the upstream transport distance of PSU subcomponents.

Final assembly The final assembly of the PSU is modeled by a fixed amount of electricity consumption for the entire BS, represented by $\mathcal{A}_{PSU}$.

As a result, the complete row vector of foreground process quantities for the PSU production module is

$$\mathbf{Q}_{PSU} = [\mathcal{E}_{conv} \quad \mathcal{E}_{batt} \quad \mathcal{M}_{PSU} \quad \mathcal{T}_{PSU} \quad \mathcal{A}_{PSU}]. \quad (6.39)$$

Note that the production of additional components (e.g., additional storage batteries, converters, etc.) required to power an isolated BS with a diesel generator or a PV system is not included in the PSU production module, but rather in the IAF calculations for the use stage.

6.3.1.5 External cable production

External cables connect the BS components. For data signal transfer, optical fibers connect the BBU to the RUs and coaxial cables connect the RUs to the AUs. For the electricity supply, power cables connect the PSU to all other active BS components.

Production of electronic subcomponents The production of each type of external cables is modeled with respect to their length. The length of data cables, denoted by $\mathcal{E}_{opt}$ for optical fibers and $\mathcal{E}_{coax}$ and coaxial cables, depends on the distance between the BBU and the AUs. For a tower-mounted BS, this distance is typically h_{BS} , the height of the tower. For one cell, the model variable that sets the relative position of the RU between the BBU and AU, denoted by δ_{cable} such that $\delta_{cable} \in [0, 1]$, defines the proportion of optical and coaxial cables used to reach the AU. This yields

$$\mathcal{E}_{opt} = h_{BS} \delta_{cable}, \quad (6.40)$$

and

$$\mathcal{E}_{coax} = N_{TRX} h_{BS} \cdot (1 - \delta_{cable}). \quad (6.41)$$

It is assumed that one optical fiber is enough for one cell. Conversely, the number of parallel coaxial cables is equal to N_{TRX} , the number of TRXs in the RU, which is also the number of antenna subarrays in the AU. As RFUs are installed in the same cabinet as the BBU, $\delta_{cable} \approx 0$, whereas for RRUs installed closer to AUs, δ_{cable} is closer to 1. Since AAUs integrate the AU and the RU in the same unit, coaxial cables are not needed, and thus $\delta_{cable} = 1$.

The length of power cables feeding the RUs is assumed to be equal to the length of optical fibers connecting the BBU to the RUs, such that

$$\mathcal{E}_{pwr} = h_{BS} \delta_{cable}. \quad (6.42)$$

Since the power cables that supply the BBU are included in the PSU production module, they are not modeled specifically as external cables.

Upstream transport and final assembly No further assembly or upstream transport is considered for external cables because they are already the end products installed on site.

As a result, the complete row vector of foreground process quantities for the external cable production module is

$$\mathbf{Q}_{cab} = [\mathcal{E}_{opt} \quad \mathcal{E}_{coax} \quad \mathcal{E}_{pwr}]. \quad (6.43)$$

6.3.2 Distribution stage

The distribution stage includes the transport of BS components from their assembly factory to the specific site where they operate, plus their installation on site. The transport is divided in two segments: (i) the international transport between the manufacturer's assembly factory and the MNO's warehouse, and (ii) the local transport between the MNO's warehouse and the BS site.

International distribution The international distribution is modeled by a mix of freight transportation means for the transported mass over the international transport distance (in kg·km), as in Equation (6.8) for the upstream transport. The transported mass is calculated by first summing the masses of all the electronic and mechanical subcomponents for each BS component. Then, the total transported mass is the sum of masses for all N_{comp} components of the BS as

$$\mathcal{M}_{comp} = \sum_{i=1}^{N_{comp}} \left(\sum_{k=1}^{\tilde{K}_i} Q_{i,k} \rho_{i,k} \right), \quad (6.44)$$

where $Q_{i,k}$ is the quantity of subcomponent k in component i , $\rho_{i,k}$ is the associated mass density if $Q_{i,k}$ is not expressed in kilograms (otherwise $\rho_k = 1 \text{ kg/kg}$), and $\tilde{K}_i$ is the total number of subcomponents in the i th component. Unlike upstream transport, the packaging is no longer considered negligible for worldwide freight. The total mass of the packaging is then calculated as

$$\mathcal{M}_{pack} = \mathcal{M}_{comp} \beta_{pack}, \quad (6.45)$$

where β_{pack} is a technological parameter representing the packaging overhead.

The international BS distribution is finally calculated (in kg·km) as

$$\mathcal{T}_{inter} = d_{inter} \cdot (\mathcal{M}_{comp} + \mathcal{M}_{pack}), \quad (6.46)$$

where d_{inter} is a model variable representing the international transport distance. This distance is set to $2 \times 10^4 \text{ km}$ by default but depends on where the BS components are manufactured and where the MNO is based.

Local distribution The local distribution is handled by a small truck dedicated to the BS installation on site. In this case, all transport impacts are allocated to the entire BS, and no longer allocated with respect to the mass as with international distribution, because the entire round trip is assumed to be dedicated solely to the BS installation. Therefore, the local distribution is simply modeled (in km) as

$$\mathcal{T}_{loc} = d_{loc}, \quad (6.47)$$

where d_{loc} is a model variable representing the round-trip distance between the MNO's warehouse and the BS site location. The model does not account for additional transportation for the technicians, who are assumed to travel in the same truck as the BS components.

On-site installation On-site installation of BS components consists of manual handling, assembly of mechanical parts, cable connections and system configuration, all of which are carried out by one or more technicians. As for the final assembly in the production stage, the on-site installation is modeled by a fixed amount of electricity consumption for the entire BS, represented by $\mathcal{A}_{inst}$.

As a result, the complete row vector of foreground process quantities for the distribution stage module is

$$\mathbf{Q}_{dist} = [\mathcal{M}_{pack} \quad \mathcal{T}_{inter} \quad \mathcal{T}_{loc} \quad \mathcal{A}_{inst}]. \quad (6.48)$$

6.3.3 Use stage

The use stage of the BS consists solely of electricity consumption since support activities, e.g., maintenance, are excluded from the scope of the model. Various electricity sources can be used to power the BS. The life-cycle model provides three typical options: the *electricity grid*, a *diesel generator*, or a *PV panel system* (see Figure 6.1). The latter two options are generally employed by isolated off-grid BSs [26, 27]. The BS power consumption may vary over time depending on its physical resource load $x(t)$, e.g., the average BS load is typically lower in the night than in the afternoon. Therefore, the BS power consumption $P_{BS}(x(t))$ is integrated over time t to calculate the energy consumption of all BS components as

$$Q_{use} = E_{use} = \int_0^{T_{life}} P_{BS}(x(t)) dt. \quad (6.49)$$

where the model variable T_{life} represents the BS lifetime (in years), which is set by default to $T_{life} = 10$ years. The BS power consumption model described in Chapter 5 is used to model $P_{BS}(x(t))$.

In practice, the BS life-cycle model is intended for use within the integrated RAN model described in Chapter 4, which takes input network usages on an

hourly basis. Therefore, the hourly average power model $\bar{P}_{BS}(\bar{x}[t_h])$, expressed as a function of the average load $\bar{x}[t_h]$ at hour t_h , is used to compute the BS energy consumption. Typically, $\bar{x}[t_h]$ ranges from 0 to 0.3, but it may evolve over the years as the overall data traffic increases. Furthermore, the integrated RAN model is designed to assess an unlimited number of network usages (i.e., from one to numerous input variables). Thus, since Equation (6.3) is linear, the total energy consumption of the BS over its whole lifetime is calculated (in Wh) based on its average power consumption with respect to the input variables as

$$E_{use} = T_{life} \cdot 365 \cdot 24 \cdot \frac{1}{N_h} \sum_{j=1}^{N_h} \bar{P}_{BS}(\bar{x}[t_h^{(j)}]). \quad (6.50)$$

where N_h is the number of hourly network usages set at the input of the integrated RAN model, and $\bar{x}[t_h^{(j)}]$ is the j th hourly average physical load.

6.3.4 End-of-life stage

The EoL stage is difficult to model due to a lack of primary data and a lack of consensus in the literature on how to model e-waste management [241]. Therefore, this stage is streamlined in the proposed BS life-cycle model (see Figure 6.1). Moreover, the model considers only formal waste management and assumes a 100% collection rate of BSs, as they are operated by companies that are subject to strict e-waste management legislation, such as the EU Directive 2012/19/EU [242].

Deinstallation and local collection The first EoL steps mirror the local part of the distribution stage, i.e., the deinstallation of the BS from the site, denoted by $\mathcal{A}_{deinst}$, and the local transport back to the MNO's warehouse (i.e., the local collection), denoted by $\mathcal{T}_{col}$. The electricity consumption for deinstallation is modeled as the BS installation, and the local collection as the local distribution, such that

$$\mathcal{A}_{deinst} = \mathcal{A}_{inst}, \quad (6.51)$$

and

$$\mathcal{T}_{col} = \mathcal{T}_{loc}. \quad (6.52)$$

Disassembly Next, all BS components are disassembled and separated into electronic subcomponents on one side, and mechanical subcomponents on the other. This step is modeled as the counterpart to the assembly of all BS components as

$$\mathcal{A}_{disas} = N_C \cdot (\mathcal{A}_{BBU} + \mathcal{A}_{RU} + \mathcal{A}_{AU}) + \mathcal{A}_{PSU}, \quad (6.53)$$

In this case, the local electricity grid mix is used rather than the electricity mix used for the final assembly of BS components.

Downstream transport Downstream transport of waste from BS subcomponents is then considered, which is modeled like upstream transport as

$$\mathcal{T}_{down} = d_{down} \cdot (\mathcal{E}_{waste} + \mathcal{M}_{waste}), \quad (6.54)$$

where $\mathcal{E}_{waste}$ and $\mathcal{M}_{waste}$ are the masses of the electronic and mechanical subcomponents, respectively. These masses are respectively calculated as

$$\mathcal{E}_{waste} = \sum_{i=1}^{N_{comp}} \left(\sum_{k=1}^{\tilde{K}_i^{elec}} Q_{i,k} \rho_{i,k} \right), \quad (6.55)$$

and

$$\mathcal{M}_{waste} = \sum_{i=1}^{N_{comp}} \left(\sum_{k=1}^{\tilde{K}_i^{mech}} Q_{i,k} \rho_{i,k} \right), \quad (6.56)$$

where $\tilde{K}_i^{elec}$ and $\tilde{K}_i^{mech}$ denote respectively the number of electronic and mechanical subcomponents in the i th BS component. No international transport is involved because waste management is assumed to occur in the same region as the BS use.

Waste management of electronic and mechanical subcomponents The final step of the EoL stage considers two waste management routes for electronic and mechanical subcomponents. The impacts of each route are assumed to be proportional to the processed waste masses, i.e., $\mathcal{E}_{waste}$ and $\mathcal{M}_{waste}$. The default route for all materials is *disposal* by incineration and landfill. This is a pessimistic modeling option because no process and associated environmental impacts can be “cut-off” from the product system. Another route is waste *recycling*. This second option is more environmentally friendly because using recycled materials reduces BS production impacts [243]. However, using the open-loop substitution approach leads to the invisibilization of recycling processes and a potential underestimation of EoL impacts [241]. Thus, the recycling route is an optimistic modeling option (especially open-loop recycling), and a realistic EoL assessment should lie somewhere between the two options.

As a result, the complete row vector of foreground process quantities for the EoL stage module is

$$\mathbf{Q}_{EoL} = \left[\mathcal{E}_{waste} \quad \mathcal{M}_{waste} \quad \mathcal{T}_{col} \quad \mathcal{T}_{down} \quad \mathcal{A}_{deinst} \quad \mathcal{A}_{disas} \right]. \quad (6.57)$$

6.3.5 Technological parameter estimation

Using the approach explained in Section 4.4, the technological parameters of each foreground process model are estimated via regression analysis of empirical data.

The goal of this approach is to provide realistic, albeit approximate, numerical values for enabling quantitative comparisons of LCIA results between different BS configurations. Based on the complete set of empirical data sources described in Section 4.4.2, this section first presents the specific dataset used to estimate the parameters of the BS life-cycle model. Then, it lists the obtained numerical parameter estimates. Supplementary material of [JP3] details how the specific regression analyses are performed and assesses the goodness-of-fit of the proposed models.

6.3.5.1 Specific empirical dataset

Two main sources of empirical data are used to estimate the technological parameters of the BS life-cycle model: internal and external hardware teardowns and technical documentation from manufacturers. Hardware teardowns reflect the actual material composition of deployed BS components but are time-consuming and require specialized tools and equipment. Technical documentation, in contrast, is available for a broader range of commercial component configurations and is easier to analyze thanks to standardized reporting. Yet, technical documentation is not guaranteed to accurately reflect the hardware materiality and may lack the granularity necessary to estimate all technological parameters. Therefore, combining the two data sources leverages their complementary strengths. For this thesis, one BBU, RU, and AU of a macrocell 4G-LTE BS were internally teardowned. Additionally, external teardowns of 15 BS components were obtained from various sources, and the collected documentation covers around 50 BS components.

Regression analysis is then used to obtain numerical parameter estimates from this empirical dataset based on several assumptions. First, when a subcomponent model corresponds to Equation (6.7), the scaling exponents are limited to $\alpha \in \{0, 0.25, 0.5, 0.75, 1\}$. Second, due to a lack of primary data, the upstream and downstream transport distances are assumed to be equal for all subcomponents of BS components, such that

$$d_{BBU}^{up} = d_{RU}^{up} = d_{AU}^{up} = d_{PSU}^{up} = d_{down} = d_{up/down} \quad (6.58)$$

where $d_{up/down} = 1000$ km, similar to the standard transport distances of electronic modules in [244]. Third, also due to a lack of primary data, the same amount of electricity consumption is assumed for assembling all BS components and for installing and deinstalling the BS, such that

$$\mathcal{A}_{BBU} = \mathcal{A}_{RU} = \mathcal{A}_{AU} = \mathcal{A}_{PSU} = \mathcal{A}_{inst} = \mathcal{A}_{deinst} = \mathcal{A}_{elec} \quad (6.59)$$

where $\mathcal{A}_{elec} = 1000$ Wh, in the same order of magnitude as [244] for the assembly of similar electronic devices. The latter two assumptions result in a wider range of uncertainty than if specific data sources were used.

Table 6.2 Technological parameter estimates for the foreground process models

Parameter	Estimate ^a	Unit	Sources ^b
<i>Baseband unit production</i>			
$\{\mathcal{E}_{link}^{ref}, \mathcal{E}_{phy}^{ref}\}$	{320, 4}	cm ²	■ △
$\{\alpha_{link}, \alpha_{phy}\}$	{0.5, 0.5}	/	■ △
τ_{DL}	1.00 (FDD) 0.75 (TDD)	/	[159, 160]
τ_{UL}	1.00 (FDD) 0.25 (TDD)	/	[159, 160]
δ_{BBP}	~0.5	/	■
β_{anci}	0.15	/	■
$\mathcal{M}_{BBU}^{ref}$	0.003	kg	■ ○
α_{BBU}	1	/	■ ○
<i>Radio unit production</i>			
$\{\mathcal{E}_{proc}^{ref}, \mathcal{E}_{TRX}^{ref}, \mathcal{E}_{PA}^{ref}\}$	{16, 10, 12}	cm ²	■ □ ○
$\{\alpha_{proc}, \alpha_{TRX}, \alpha_{PA}\}$	{0.5, 0.5, 0.5}	/	■ □ ○
$\mathcal{E}_{sup}^{ref}$	350	cm ²	■ □ ○
$\mathcal{M}_{RU}^{ref}$	0.35	kg	■ ○
α_{RU}	0.5	/	■ ○
<i>Antenna unit production</i>			
$\mathcal{E}_{AU}^{ref}$	0.3	kg	■
G_{AE}	7 (w/o ABF) 5 (ABF)	dBi	■ ○ [194, 195]
β_v	0.7	/	■ ○ [194, 195]
β_h	0.7 (w/o ABF) 0.5 (ABF)	dBi	■ ○ [194, 195]
$\mathcal{M}_{AU}^{ref}$	0.004 (tradi.) 0.001 (AAU)	kg	■ ○
α_{AU}	1	/	■ ○
<i>Power supply unit production</i>			
$\{\mathcal{E}_{conv}^{ref}, \mathcal{E}_{batt}^{ref}\}$	{0.001, 0.900}	kg	□ ○
$\{\alpha_{conv}, \alpha_{batt}\}$	{1, 0.5}	/	○
β_{margin}	~0.25	/	○
$\mathcal{M}_{PSU}^{ref}$	2.3	kg	○
α_{PSU}	1	/	○
<i>Distribution stage</i>			
β_{pack}	0.3	/	○
<i>Multi-module</i>			
$\{\rho_{PCBA}, \rho_{opt}, \rho_{coax}, \rho_{pwr}\}$	{0.001, 0.004, 0.090, 0.160}	kg/cm ²	■ ○
$d_{up/down}$	~1000	km	[244]
$\mathcal{A}_{elec}$	~1000	Wh	[244]

^a Estimates with higher uncertainty indicated with a "~".^b ■ = internal hardware teardowns, □ = external hardware teardowns, ○ = technical documentation, and △ = practical network configuration.

6.3.5.2 Numerical parameter estimates

The numerical estimates for the technological parameters of the BS life-cycle model are provided in Table 6.2. This table also identifies the specific empirical data sources and literature references used to estimate each parameter. Most of the parameters in the table are associated with a specific LCA module, while the multi-module parameters are used in different modules.

The PCBA area of all subcomponents scales with the square root of their respective scaling variables. Additionally, their mass density is $\rho_{PCBA} = 0.001 \text{ kg/cm}^2$, regardless of the function performed. Sub-linear scaling also applies to the mass of mechanical structure of the RU relative to the total PCBA area. This suggests that RU manufacturers use three-dimensional spatial arrangements of PCBAs to keep the RU compact. Otherwise, the scaling would be roughly linear. In contrast, the mass scaling of the mechanical structures of BBU, AU, and PSU is linear because the size of their embedded electronic subcomponents increases only in two dimensions. Overall, these findings underlines the importance of considering nonlinear parametric models for the foreground process quantities.

In AUs, the AE gain is estimated at 7 dBi without ABF and 5 dBi with ABF. This difference is due to the reflectors located behind the AEs in traditional AUs without ABF, focusing their sector-wide beams further in the horizontal plane. However, these reflectors are not used with ABF because they interfere with the RF signal combination that enables narrow beam formation. With ABF, the horizontal AE spacing is estimated at 0.5λ , which facilitates ABF implementation. Without ABF, this spacing is estimated at 0.7λ , which reduces spatial correlation between vertical antenna subarrays. The vertical AE spacing is 0.7λ in both cases, providing a good trade-off between a narrower vertical beam width and greater side lobes [194, 195]. With AAUs, the reference mass of the mechanical subcomponents in the AU production module is lower than with traditional AUs. This difference occurs because AU production only includes the radome of AAUs, while the rest of its structure is accounted for in the RU production module.

6.3.6 Uncertainty quantification

As introduced in Section 4.4.3, lognormal distributions are used in the integrated RAN model to represent uncertainty. This uncertainty consists of two parts: variability in the empirical data, and potential error introduced by the proposed modeling approach. For the FPI, the variability part of the uncertainty is quantified based on the spread of residuals from the regression analysis. To calculate the associated GSD, a lognormal distribution is fitted to the normalized residuals relative to the predicted quantity of foreground process, setting the median of the distribution to 1. Next, the error part is quantified by estimating a multiplicative error factor based on authors' judgments. In practice, error factors of 1.25, 2, and 10 represent respectively high, medium, and very low confidence levels, with corresponding GSDs of $\sqrt{1.25} = 1.12$, $\sqrt{2} = 1.41$ and $\sqrt{10} = 3.16$.

Table 6.3 Geometric standard deviations of foreground process inventory uncertainties

(Type of) foreground process	Variability	Error ^a	Total
Electronic subcomponent production	1.41	1.12	1.44
Mechanical subcomponent production	1.41	1.12	1.44
Upstream and downstream transports	-	3.16	3.16
Distribution and collection transports	-	-	-
(Dis)assembly and (de)installation	-	3.16	3.16
Energy consumption (use stage)	1.13	1.12	1.18
Waste management routes	-	1.41	1.41

^a Based on authors' judgments.

Table 6.3 provides the GSDs representing uncertainty in the FPI for each (type of) foreground process. First, these uncertainty factors are presented separately for the variability and error part to distinguish statistically calculated GSDs from GSDs based on authors' judgments. Then, the total GSD is calculated from the GSDs of both parts, as explained in Section 4.4.3. The GSDs for variability in the production of electronic and mechanical subcomponents are estimated to be approximately 1.41 (see supplementary material of [JP3]). For use-stage energy consumption, the variability GSD corresponds to the GSD for overall uncertainty in the BS power model (see Section 5.6).

Furthermore, variability cannot be quantified for processes lacking a primary data source (e.g., assembly), resulting in less confidence in their modeling. For example, the error GSD for upstream and downstream transports is 3.16, indicating very low confidence in the estimated transport distance. Given that the corresponding multiplicative error factor is 10 and that the estimated distance $d_{up/down} = 10^3$ km (see Table 6.2), these transport distances are expected to be within the 10^2 - 10^4 km range with 95% confidence. In addition, uncertainty quantification does not apply to distribution and collection transports at the FPI level because their distances are direct configuration variables of the model (i.e., d_{inter} and d_{loc}).

6.4 Impact assessment factors

The environmental impacts of the BS life cycle are calculated based on the IAFs that constitute the matrix $\mathbb{F}_m(\varphi)$ for each LCA module. These IAFs correspond to background processes that are built on unit processes from the ecoinvent database. The main data sources for developing the background processes are the hardware teardowns and the technical documentation of BS components. However, these empirical data sources do not provide sufficient information to develop parametric background processes. Therefore, it is assumed that IAFs are constant, which introduces additional uncertainty in the model.

For most background processes, “market for” unit processes are used to represent the average market composition and include prior transport. Global average unit processes (i.e., “GLO” processes in ecoinvent) are used either when the process value chain is assumed to be global, when the location of the process is unknown, or when a regionalized unit process is unavailable in ecoinvent. For background processes with specific raw material mixes, custom unit processes were developed to adjust the ratio of virgin to recycled materials. Due to limitations in ecoinvent (e.g., lack of specific items, outdated process models, etc.), additional custom unit processes were developed to model the production of ICs, connectors, and PAs. Supplementary material of [JP3] provides further details on how the background processes and custom unit processes were built based on ecoinvent.

The rest of this section discusses the IAFs presented in Figure 6.2 for all foreground processes. This figure focuses on climate change, for which the specific indicator is the GWP expressed in kgCO₂eq. A similar figure for mineral and metal resource use, for which the specific indicator is abiotic resource depletion potential (ADP) expressed in kgSb-eq, is provided in Appendix A.6.

6.4.1 Printed circuit board assemblies

A PCBA consists of a printed circuit board (PCB) on which active and passive electronic components are mounted. Most of the active components are logic and memory ICs, while passive components are mainly inductors, capacitors, resistors, and connectors. The type and density of electronic components depend on the function performed by the PCBA. Consequently, specific IAFs are calculated for the different types of PCBAs considered in the FPI. Figure 6.2(a) shows that the GWP per square-centimeter of PCBA area ranges from 0.03 kgCO₂eq for basic analog functions to 0.25 kgCO₂eq for computation-intensive digital functions. This difference is explained by the high density of high-impact components in the BBU boards, e.g., digital ICs (for logic and memory), whereas PCBAs performing analog functions, e.g., TRXs and PAs, have a moderate component density. Yet, ICs implementing analog functions still have high manufacturing impacts due to the use of precious metals such as gold and silver. PCBAs supporting power supply and ancillary functions have low to moderate GWP, reflecting a high density of low-impact components, e.g., capacitors, inductors, and small ICs. The PCB mounting processes and solder paste are also considered in IAF calculations for PCBAs.

6.4.2 Other electronics

In the AU, internal coaxial cables transmit the signal from the external connectors to the AEs through the delay lines. These delay lines consist of a non-populated PCB and a few polymer parts housed in a die-cast aluminum casing. The radiating elements of AEs are primarily made up of aluminum sheets and polymer parts. It is assumed that only primary aluminum is used to manufacture AEs as they

require high purity to avoid degrading RF signals [238]. Figure 6.2(b) shows that the aluminum accounts for $> 80\%$ of the GWP of AEs.

In the PSU, the two electronic subcomponents are modeled using proxies from ecoinvent scaled according to their mass. The power converters are approximated by a unit process that models the production of a PV system inverter, comprising transformers, control units, connectors, etc, assuming that BS power converters have a similar composition. In Figure 6.2(b), the impact from copper in power converters is due to the internal wires. Then, the backup batteries are modeled as an equal mix of lithium-ion and lead-acid batteries, as these two technologies coexist in practice for PSUs of BSs. Since lithium-ion batteries have a higher energy density than lead-acid batteries, they also have a higher GWP per kilogram.

6.4.3 Mechanical subcomponents

The mechanical subcomponents are made of metal and polymer parts. The metal parts mainly consists of aluminum, steel, iron, and copper. The polymer parts are made of acrylonitrile-butadiene-styrene, and polyamide is used for glass fiber-reinforced plastic. All mechanical subcomponent materials are modeled using a certain amount of raw material from the technosphere (including processing losses), coupled with a unit process that models the material processing, e.g., injection molding for polymers. The life-cycle model provides two options for raw materials sourcing (see Section 6.3.1): a market mix or a specific mix containing more recycled materials. The market mixes modeled by ecoinvent are assumed for all materials by default, while specific material mixes require custom modeling.

In the proposed life-cycle model, the specific raw material mix only applies to aluminum because ecoinvent provides a unit process for aluminum scrap recycling, unlike for other materials. However, this limitation is balanced by the fact that aluminum accounts for most of the GWP in mechanical subcomponents. The closed-loop recycling scenario for aluminum assumes an optimistic recycling efficiency of 95%. This means that 95% of the aluminum mass is recovered through recycling and used to produce new BS components, while the remaining losses are compensated for with additional aluminum from the market.

The PSU and BBU casings are typically made of steel and aluminum sheets, while the RU casing is made of die-cast aluminum. An internal part of the RU structure is copper-plated to implement cavity filters. Conversely, the radome of traditional AUs is made of reinforced plastic and is mounted on an aluminum structure that includes the reflective plane. For AAUs, only the radome is included in the AU module since the rest of the structure is modeled by the RU mechanical structure. Figure 6.2(c) shows that the GWP of mechanical subcomponents ranges from 6 to 18 $\text{kgCO}_2\text{eq/kg}$ with the market mix of raw materials, and from 2 to 12 $\text{kgCO}_2\text{eq/kg}$ with the specific raw material mix. This demonstrates that using more recycled aluminum reduces the GWP of mechanical structures by one-third to two-thirds compared to using an average market mix of raw aluminum.

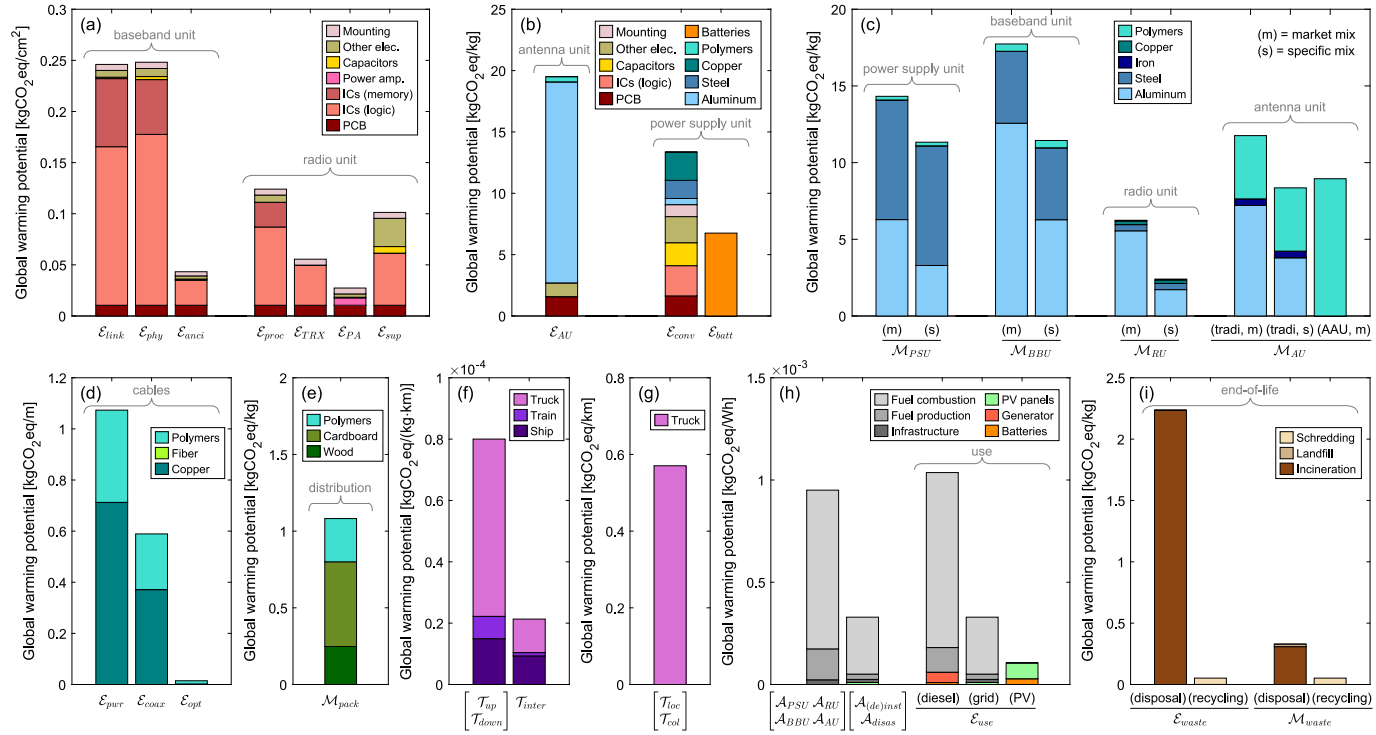


Fig. 6.2 Global warming potential for all foreground processes: (a) printed circuit board assembly production, (b) other electronic production, (c) mechanical structure production, (d) cable production, (e) packaging production and disposal, (f) freight transport, (g) local transport, (h) electricity consumption, and (i) waste management routes. Some impact assessment factors apply to multiple foreground processes [*in brackets*], while different impact assessment factors can be assigned to a single process depending on the model options (*in parentheses*).

6.4.4 External cables

Since the ecoinvent database lacks the necessary granularity and specificity for modeling cable production, custom unit processes were developed for the production of external BS cables. Figure 6.2(d) shows that the GWP per meter of cable is dominated by copper when present, which is the case for coaxial and power cables. Furthermore, the GWP per meter of optical fiber and power cables differs by two orders of magnitude. In fact, this partly reflects the difference in linear density between all these cables (see Table 6.2).

6.4.5 Packaging and transport

The packaging mainly consists of wooden pallets, corrugated cardboard boxes and other polymers. Yet, cardboard and polymers account for most of the packaging's GWP, as illustrated in Figure 6.2(e). Upstream transport of BS subcomponents and downstream transport of waste are both modeled using a combination of freight transportation means, such as trucks, trains, inland barges, and container ships. International transport primarily consists of container ship freight, with minor contributions from truck and train. Road transport has the highest GWP, around $0.16 \text{ kgCO}_2\text{eq}/(\text{t}\cdot\text{km})$, compared to around 0.05 and $0.01 \text{ kgCO}_2\text{eq}/(\text{t}\cdot\text{km})$ respectively for rail and container ships. In Figure 6.2(f), the GWP per kilogram-kilometer of upstream and downstream transports are higher than that of the international transport due to the higher share of road transport. Furthermore, Figure 6.2(g) shows the GWP per kilometer for the local distribution and collection, which is handled exclusively by a small truck dedicated to transporting BS components.

6.4.6 Electricity consumption

The electricity consumed by the final component assembly is modeled using the medium-voltage electricity grid mix in China, assuming that BS components are manufactured and assembled in East Asia [245]. Conversely, the European low-voltage grid mix models the electricity used for installing, deinstalling, and disassembling the BS. Since the associated IAFs only applies to BSs deployed in Europe, they must be adapted for deployment in other regions. The life-cycle model proposes three options for powering the BS during the use stage: the electricity grid (default option), a diesel generator, or a PV panel system. The European electricity grid mix applies to the default option for a BS deployment in Europe. For diesel power generation, IAFs include the impacts of producing the generator, the fuel and the necessary additional batteries, as well as the direct emissions from fuel combustion. Finally, the PV system model includes the production of PV panels as well as additional batteries.

The IAFs for electricity consumption are calculated per watt-hour of energy consumed, and those for electricity grids are taken directly from ecoinvent. Figure 6.2(h) shows a GWP of around 1000, 950, 330 and $100 \text{ gCO}_2\text{eq}/\text{kWh}$ for re-

spectively the diesel generator, Chinese grid, European grid and PV system. Direct emissions dominate the GWP when electricity is generated partly from fossil fuels. The GWP of electricity in China is very high because coal is the main energy source, whereas in Europe more renewable and nuclear energy sources are used in addition to fossil gas [246]. Conversely, the GWP of the PV system is mainly due to PV panel production. Thus, the associated IAFs are largely influenced by the system lifetime, which is assumed to be 30 years – longer than the typical BS lifetime.

6.4.7 Waste management

Two different routes are modeled for the management of waste from electronic and mechanical subcomponents. The first route corresponds to disposal by incineration and landfill. To calculate the corresponding IAFs, unit processes are selected in ecoinvent based on the mass composition of waste: ~70% aluminum, ~10% polymers, and ~20% of other materials for mechanical subcomponents, and ~35% PCBAs, ~40% batteries, and ~25% cables for electronic subcomponents. The second waste management route is recycling, which is modeled the same way for both types of waste. This route involves shredding waste with a 95% material recovery rate, leaving 5% of the waste to be landfilled. The subsequent processes are cut off from the product system in open-loop recycling, whereas they are considered production processes in closed-loop recycling.

Figure 6.2(i) shows that most of the GWP of the disposal route comes from the incineration. The GWP of e-waste incineration also exceeds that of waste from mechanical subcomponents because e-waste contains more materials to burn and thus emits more GHGs. For both types of waste, the GWP of the recycling route is mainly due to shredding [244], and is at least one order of magnitude lower than the GWP of the disposal route.

6.4.8 Uncertainty quantification

As introduced in Section 4.4.3, lognormal distributions are used in the integrated RAN model to represent uncertainty. Similar to the FPI, the total uncertainty in IAFs consists of a variability and an error part. However, variability in IAFs cannot be directly calculated from empirical data because IAFs are mainly based on a single teardown. Instead, the total uncertainty of IAFs captures (i) the expected variability of process composition, and (ii) the confidence in background process modeling based on ecoinvent. Therefore, the GSDs for both the variability and error parts are estimated based on the authors' judgments. As for the FPI, multiplicative error factors of 1.25, 2, 3.16 (i.e., an order of magnitude) and 10 are assumed for high, medium, low, and very low confidence levels. The corresponding GSDs are $\sqrt{1.25} = 1.12$, $\sqrt{2} = 1.41$, $\sqrt{3.16} = 1.78$ and $\sqrt{10} = 3.16$, respectively.

Table 6.3 provides the GSDs representing both the expected variability and error parts of the IAF uncertainty for each (type of) foreground process. The total

Table 6.4 Geometric standard deviations of impact assessment factor uncertainties

(Type of) foreground process	Variability ^a	Error ^a	Total
Electronic subcomponent production	1.41	1.12	1.44
Mechanical subcomponent production	1.78	1.12	1.80
Upstream and downstream transports	1.78	1.12	1.80
Distribution and collection transports	1.12	1.12	1.17
(Dis)assembly and (de)installation	1.12	1.12	1.17
Energy consumption (use stage)	1.12	1.12	1.17
Waste management routes	1.78	3.16	3.62

^a Based on authors' judgments.

GSD is then calculated from the GSDs of both parts, as explained in Section 4.4.3. Variability in the composition of distribution and collection transports, as well as electricity consumption for (dis)assembly, (des)installation, and in use stage, is expected to be low, implying a low GSD. In contrast, a high variability is assumed in the composition of mechanical subcomponent production, upstream and downstream transports, and waste management routes, implying a higher GSD.

Regarding the error part of uncertainty, the level of confidence in the modeling is generally high because the background processes are modeled in detail using ecoinvent. Yet, streamlined waste management modeling is given a very low confidence level. Note that this uncertainty quantification only addresses model-specific uncertainty but not external uncertainty (e.g., in ecoinvent modeling).

6.5 Results for typical configurations

This section performs the interpretation phase of the LCA methodology by applying the BS life-cycle environmental impact model to the five typical BS configurations identified in Section 4.5. Before comparing the assessment results for all typical BS configurations, this section examines in detail the LCIA results for one specific BS configuration. The section also performs an uncertainty analysis. All typical configurations examined in this section correspond to single-band BSs. In practice, however, most BSs deployed in RANs support multiple frequency bands. As a first approximation, the LCIA results of a multi-band BS can therefore be obtained by summing the impacts of the corresponding single-band configurations. This approximation is justified by the BS modeling approach, in which each cell is generally represented independently. Further examination of LCIA results for multi-band BS configurations is provided in Chapter 7.

In this section, LCIA results are calculated for a specific FU defined as *the provision of all wireless communication services by one BS deployed in Europe throughout its whole lifetime*. By default, the use-stage energy consumption is supplied by the electricity grid (represented by the average mix in Europe), no recycling is assumed

at the EoL stage, and thus no specific mix of raw materials is assumed at the production stage. To assess the use stage, an average physical resource load of 0.1 is assumed, and PSSs are not considered. Thus, most of the energy consumed by the BS originates from static power consumption. Since the five typical BS configurations do not provide the same QoS, studying QoS-oriented FUs could also be relevant for fairly comparing the configurations.

6.5.1 Configuration-specific analysis

The configuration-specific analysis focuses on *Ma-L18*. First, this configuration is assessed across multiple environmental impact categories. Next, the effects of the BS life-cycle model options are studied for this configuration.

6.5.1.1 Multi-indicator assessment

The LCIA results for *Ma-L18* are reported in Figure 6.3 across all environmental impact categories of the EF 3.1 method [197].

Figure 6.3(a) focuses on the production stage and breaks down the impacts by BS component. Hotspot analysis reveals that the RUs dominate most impact categories (20-45%), due to their electronic subcomponents, aluminum casing, and the fact that three of these components are installed in the BS to cover its three sectors. The BBU also contributes significantly to BS production impacts (10-50%), due to its electronic subcomponents. The large contribution of external cables in certain impact categories (up to 50%) comes from power cables containing a substantial amount of copper. The impacts of electronic subcomponents are mainly due to PCBA manufacturing, especially ICs, while the impacts of mechanical subcomponents are mainly due to aluminum production. Upstream transport and final component assembly have a negligible impact in all categories.

Next, Figure 6.3(b) extends the LCIA results to the four life-cycle stages of *Ma-L18*. With the European electricity grid mix and a 10-year lifetime, its use stage dominates the other life-cycle stages in all impact categories (55-99%). The production stage is the second largest contributor to impacts (typically 10-20%), with up to 45% of mineral and metal resource use. The limited contribution of the production stage results from the relatively long lifetime and high power consumption of this macro BS. However, this could differ for smaller BSs, which would consume less power during use and have shorter lifetimes. The contributions of distribution and EoL stages are marginal across all impact categories (i.e., <5% each).

6.5.1.2 Effects of the model options

For each option of the BS life-cycle model, Figure 6.4 shows the LCIA results per life-cycle stage for *Ma-L18*. At the production stage, the proposed life-cycle model allows for two mixes of raw materials: a market mix or a specific mix. There are also two waste management routes at the EoL stage: disposal or recycling. Additionally, the use stage supports three power supply sources: a diesel generator,

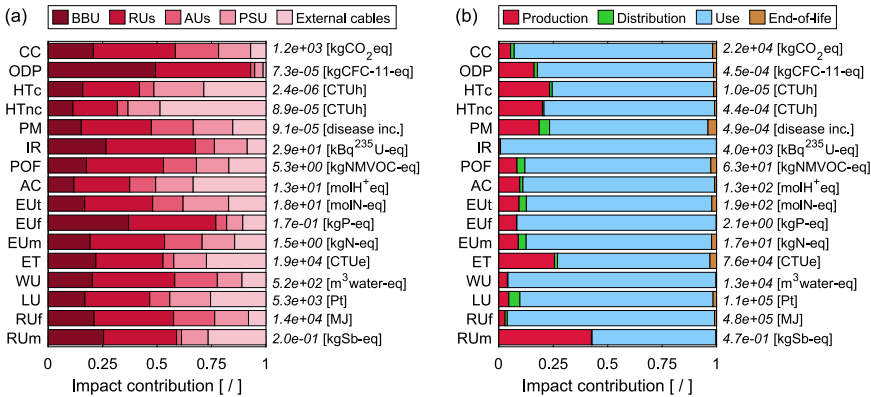


Fig. 6.3 Life cycle impact assessment results for (a) the production stage only, and (b) all life-cycle stages of *Ma-L18* configuration. Radio units (RUs) and baseband unit (BBU) contribute to most production impacts, sometimes with external cables, unlike antenna units (AUs) and power supply unit (PSU). The use stage largely dominates total impacts, followed by the production stage. (CC=climate change, ODP=ozone depletion, HTc/nc=human toxicity - cancer/non-cancer, PM=particulate matter, IR=ionizing radiation, POF=photochemical ozone formation, AC=acidification, EUt/f/m=eutrophication - terrestrial/freshwater/marine, ET=ecotoxicity freshwater, WU=water use, LU=land use, and RUF/m=resource use - fossils/minerals and metals)

the electricity grid, or a PV system. Yet, the life-cycle model does not provide any specific option for the distribution stage.

Figure 6.4(a) examines the effects of model options on the climate change using the GWP indicator. First, it shows that using more recycled raw materials to produce BS components, as well as recycling BS components at the end of their life cycle, reduces the GWP of associated life-cycle stages by -20% . Second, using a diesel generator to power the BS results in a GWP that is $\times 3.1$ the GWP of powering the BS from the grid, increasing the use stage contribution to 97% of the total GWP of the BS. Conversely, powering the BS with a PV system reduces the GWP of the use stage by -70% , bringing its contribution down to 77% of the total GWP. Thus, regardless of the power supply option, the use stage remains dominant, ranging from 6 to 60 tCO₂eq. In comparison, recycling and using recycled raw materials only reduce the total GWP of the BS by -0.3 tCO₂eq together.

Next, Figure 6.4(b) shows how the model options affect the use of mineral and metal resources through the ADP indicator. This second impact category was selected because it exhibits the most contrasting results with respect to GWP. In this category, the distribution and EoL stages are negligible compared to the production and use stages. Counterintuitively, increased use of recycled materials for BS production has no effect on ADP. This result arises from specific recycling processes that require precious metals (according to ecoinvent modeling).

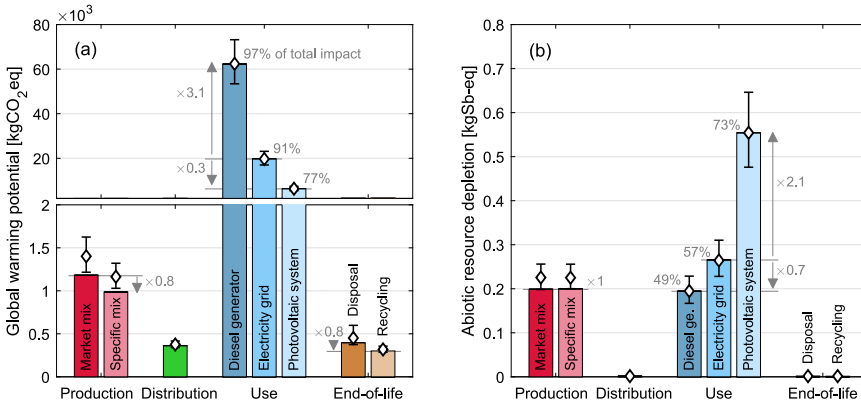


Fig. 6.4 Effects of the life-cycle model options on (a) climate change, and (b) mineral and metal resource use of the *Ma-L18* configuration. Results demonstrate possible burden shifting between impact categories, indicating trade-offs for base station designs.

Unlike the effects on GWP, using a diesel generator to power the BS reduces the ADP of the use stage by -30% compared to powering the BS using the electricity grid (whose ADP is dominated by the copper in distribution networks). This brings the use stage contribution to 49% the total life-cycle ADP. In contrast, powering the BS with the PV system uses $\times 2.1$ mineral and metal resources for the PV panels and attached batteries than using the electricity grid, raising the use stage contribution to 73% of the total ADP. Therefore, Figure 6.4 demonstrates possible burden shifting between impact categories, indicating trade-offs for BS designs. This underscores the importance of employing multi-indicator LCIA methods.

6.5.2 Cross-configuration analysis

The cross-configuration analysis now compares the environmental impacts of the five typical BS configurations. First, the analysis focuses on the production stage. Then, it extends to the assessment of LCIA results for all life-cycle stages. A final analysis performs the optional normalization and weighting steps of LCA in order to assess aggregated environmental footprint scores. Before further analysis, it is important to note that the five typical configurations do not provide the same capacity or transmit power per cell. Therefore, they do not provide identical QoS in terms of data throughput per UE and coverage. In particular, the *Mi-L18* configuration is primarily intended for dense urban deployments, with approximately $\times 10$ - 20 the density of macro BSs.

6.5.2.1 Production stage assessment

The environmental impacts of typical BS configurations during the production stage are presented in Figure 6.5 for selected impact categories.

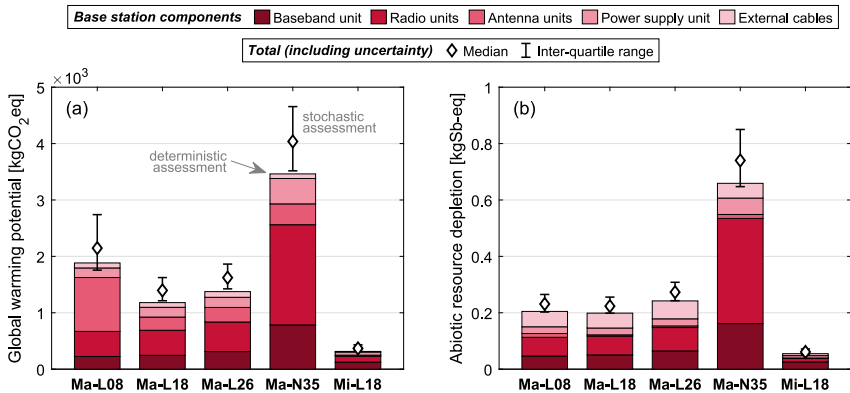


Fig. 6.5 Impacts of the production stage for five typical base station configurations on (a) climate change, and (b) mineral and metal resource use. Impacts are similar for the three macro 4G-LTE configurations, $\times 2$ -3 for the macro 5G-NR configuration, and $\times 1/5$ for the micro 4G-LTE configuration. Radio units are the hotspot for both impact categories.

Figure 6.5(a) focuses on the climate change and shows that the GWP of producing traditional macro 4G-LTE BS ranges from 1200 to 1900 kgCO₂eq, compared to about 3500 kgCO₂eq for *Ma-N35*, the 5G-NR configuration. The GWP of producing *Mi-L18* is significantly lower, at around 300 kgCO₂eq. This reflects the greater transmit power of macro BSs, especially *Ma-N35*, which require larger RUs and PSUs than in the micro BS. The higher antenna gains of macro BSs also require more AEs and hence larger AUs, especially for *Ma-L08*, where the greater wavelength increases AE size. For *Ma-N35*, the 64 TRXs occupy a significant PCBA area in RUs and its AAUs comprise a large number of AEs. Conversely, using AAUs instead of traditional RUs plus AUs reduces the GWP for casing production. The large capacity of *Ma-N35* also increases the GWP of BBU production.

Still focusing on the production stage, Figure 6.5(b) examines the use of mineral and metal resources. In general, the relative comparison of the ADP for producing the typical BS configurations is similar to that of the GWP. The ADP for producing traditional macro 4G-LTE BS is 0.20-0.25 kgSb-eq, 0.65 kgSb-eq for *Ma-N35*, and 0.05 kgSb-eq for *Mi-L18*. Compared to the GWP, the contribution of mechanical subcomponent production is lower for ADP, reducing the AU contribution to a small fraction. Meanwhile, the contribution of PCBA and power cables to ADP increases, particularly due to the use of copper and gold.

6.5.2.2 Full life-cycle assessment

The total environmental impacts of the five typical BS configurations throughout their full life cycle are presented in Figure 6.6 for selected impact categories.

Figure 6.6(a) focuses on the climate change and shows that the total GWP is

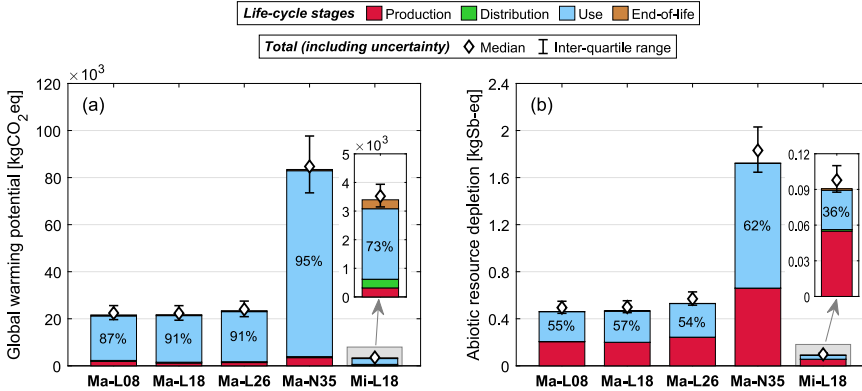


Fig. 6.6 Impacts of all life-cycle stage for five typical base station configurations on (a) climate change, and (b) mineral and metal resource use. Impacts are similar for the three macro 4G-LTE configurations, $\times 4$ for the macro 5G-NR configuration, and $\times 1/5$ for the micro 4G-LTE configuration. The use stage is a hotspot for both impact categories and the production stage is another hotspot for mineral and metal resource use.

about 22 tCO₂eq for traditional macro 4G-LTE BSs, 85 tCO₂eq for the macro 5G-NR BS, and 3.5 tCO₂eq for the micro BS. The use stage is clearly the hotspot and accounts for 87-91% of total GWP for macro 4G-LTE BSs, 95% for *Ma-N35*, and 73% for *Mi-L18*. The lower contribution of the use stage for *Mi-L18* arises from its lower power consumption and shorter lifetime. The production stage then accounts for < 15% of the total GWP in all configurations. Finally, the GWP of the distribution and EoL stages are largely negligible in macro BSs (i.e., < 2% each), while they constitute around 10% of the total GWP each in *Mi-L18*. In practice, the impacts of these two stages mainly result from local transport (i.e., local distribution and collection). However, it is important to note that PSSs are neglected in these results. Thus, implementing PSSs could reduce the contribution of the use stage to the total GWP, and vice versa for the other stages.

Next, Figure 6.6(b) focuses on the use of mineral and metal resources and shows that the production stage is another hotspot in this category, accounting for 38-46% of the total ADP of macro BSs, and up to 61% for the micro BS. Therefore, the production stage cannot be overlooked with regard to ADP when planning RAN deployment strategies. The total ADP is around 0.5 kgSb-eq for macro 4G-LTE BSs, 1.7 kgSb-eq for *Ma-N35*, and 0.1 kgSb-eq for *Mi-L18*. In all typical BS configurations, the distribution and EoL stages do not significantly contribute to the total ADP.

Overall, these results suggest that the most effective strategy for reducing the total impact of BSs on climate change is to decarbonize the electricity supply. In addition, reducing the use of mineral and metal resources by BSs mainly involves reducing the amount of metals needed to produce BS components (especially pre-

cious metals in electronic subcomponents), as well as reducing the amount of metals needed to generate the electricity that supplies BSs.

6.5.2.3 Environmental footprint score

A comprehensive analysis of BS life-cycle environmental impacts requires examining all impact categories and potential shifts in burden between them. However, interpreting all characterized LCIA results can be difficult for two reasons. First, understanding the impact indicators and the underlying environmental mechanisms is not necessarily straightforward (e.g., is 1 kgSb-eq of ADP significant?). Second, the environmental indicators cannot be directly compared with each other (e.g., is reducing GWP by $-100 \text{ kgCO}_2\text{eq}$ worthwhile if it increases ADP by $+0.5 \text{ kgSb-eq}$?). To address these issues, the LCA methodology proposes two optional steps in the impact assessment phase: normalization and weighting.

Normalization aims to compare characterized LCIA results to a single reference situation for all impact categories. In EF 3.1, the reference for all categories is the global average impact per person in 2010 [197]. Figure 6.7(a) shows the normalized LCIA results for the entire life cycle of *Ma-L18*, expressed in person-years ($\text{pers}\cdot\text{yr}$)³. For instance, this shows that its GWP of $22 \text{ tCO}_2\text{eq}$ corresponds to 3 pers-year, and that its ADP of 1.7 kgSb-eq corresponds to approximately 7.5 pers-year. This indicates that the BS uses $\times 7.5$ the mineral and metal resources used by one person in 2010, while its impact on climate change is $\times 3$ that of one person in 2010. The use of fossil resources by the BS is also 7.5 pers-year, while most other impact categories are < 3 pers-year. However, normalized LCIA results do not indicate whether, e.g., an ADP of 7.5 pers-year is worse than a GWP of 3 pers-year. They also do not readily support decision-making and strategy planning aimed at capturing the full environmental footprint of the BSs.

Weighting then assigns a specific weight to each environmental impact category, enabling comparison and aggregation of LCIA results across categories. Figure 6.7(b) shows the set of weights proposed by the EF method [235]. Climate change receives the highest weight of 0.21, followed by water use, land use, fossil resource use, and mineral and metal resource use, weighted around 0.09. Particulate matter also receives a weight around 0.09, while the weights of the other categories are smaller. These weights were determined using a hybrid evidence- and judgment-based approach that reflect how environmental challenges were perceived in Europe in 2018 [235]. Thus, weights may change over time and differ by region, depending on environmental priorities. Therefore, the weighting step inherently involves some subjectivity, and the weight values are open to debate.

Figure 6.7(b) also shows the weighted LCIA results of *Ma-L18* for each impact

³Each impact category is expressed in a specific unit (e.g., kgCO_2eq) and normalization divides the results for each category by the corresponding impact of one person during one year (e.g., $\text{kgCO}_2\text{eq}/\text{pers}/\text{year}$). Thus, the normalized results are expressed in the same unit for all impact categories (e.g., $\text{kgCO}_2\text{eq}/(\text{kgCO}_2\text{eq}/\text{pers}/\text{year}) = \text{pers}\cdot\text{year}$).

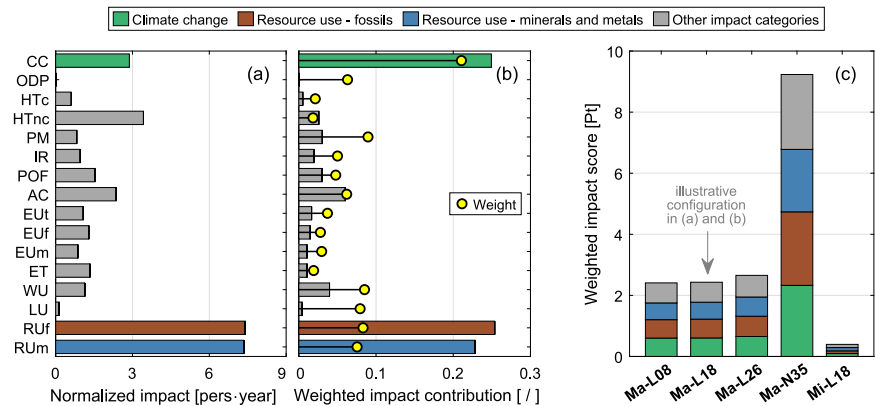


Fig. 6.7 Aggregation of life cycle impact assessment results into a single environmental footprint score: (a) normalized results and (b) weighted results for the *Ma-L18* configuration, and (c) single impact scores for the five typical base station configurations. Climate change, fossil resource use, and mineral and metal resource use each account for around 1/4 of the overall environmental footprint of these base stations. (CC=climate change, ODP=ozone depletion, HTc/nc=human toxicity - cancer/non-cancer, PM=particulate matter, IR=ionizing radiation, POF=photochemical ozone formation, AC=acidification, EUt/f/m=eutrophication - terrestrial/freshwater/marine, ET=ecotoxicity freshwater, WU=water use, LU=land use, and RUF/m=resource use - fossils/minerals and metals)

category, relative to a unit sum. These results indicate that its impact on climate change is similar to its impacts on the use of fossil resources and on mineral and metal resources, according to EF weighting. These three impact categories each represent approximately 1/4 of the total environmental footprint of this BS configuration, justifying the primary focus on these categories. The remaining 1/4 comprises the other 13 impact categories. Since the categories of fossil resource use and climate change are strongly correlated, efforts should focus on reducing impacts on climate change and on the use of mineral and metal resources to minimize the BS environmental footprint.

As a result, a single environmental footprint score is obtained by aggregating the weighted impacts across all categories. With the EF method, this score is expressed in points (Pt), and a score of 1 Pt corresponds to the environmental footprint of one average person in 2010. Figure 6.7(c) shows the weighted impact scores for the five typical BS configurations. The figure reveals that the environmental footprints of the three macro 4G-LTE configurations are 2-3 Pt, the footprint of *Ma-N35* is 9 Pt, and the footprint of *Mi-L18* is 0.5 Pt. Due to the significant contributions of the climate change and resource use categories in the weighting step, comparing the environmental footprint scores of the typical BS configurations is similar to comparing their GWP or ADP in Figure 6.6.

6.5.3 Uncertainty analysis

In addition to deterministic impact assessments, stochastic assessment results are calculated using Monte Carlo simulations to reflect the model uncertainty. Figures 6.4, 6.5, and 6.6 display the median and IQR of their respective stochastic impact assessments. However, uncertainty is not calculated for the environmental footprint scores because the weighting approach introduces substantial subjectivity that makes uncertainty calculations meaningless. Similar to the BS power model, uncertainties between different BS components (e.g., RU and AU) are assumed to be independent, whereas uncertainties within the same component type (e.g., all RUs) are assumed to be fully correlated.

In Figure 6.5, the average IQRs for GWP and ADP of the production stage alone are respectively $-14\%/+18\%$ and $-12\%/+15\%$ with respect to the medians. Regarding the overall uncertainty in Figure 6.6, the corresponding average IQRs are respectively $-12\%/+14\%$ and $-10\%/+11\%$. Thus, the spread of overall uncertainty is similar to that of the production stage alone. Most of the result uncertainty stems from uncertainties in the FPI and IAFs related to the production of electronic and mechanical subcomponents and the use-stage energy consumption. Interestingly, the high uncertainty in upstream transport and final assembly (see Tables 6.3 and 6.4) is not strongly reflected in the overall uncertainty due to their very small contribution to total BS environmental impacts.

Since lognormal distributions have positive skewness, the sum of their individual medians is smaller than the median of their combined sum. Therefore, the medians of stochastic assessments are always greater than the corresponding deterministic assessments. In Figure 6.5, this difference is about $+15\%$ and $+10\%$ for GWP and ADP of the production stage alone, and approximately $+3\%$ and $+7\%$ for the total GWP and ADP in Figure 6.6. Since the use stage dominates the total BS impacts, the distributions of the stochastic assessments are similar for the use stage alone and for the aggregation of all life-cycle stages. This explains why the stochastic assessment medians are closer to the deterministic assessments in Figure 6.6 than in Figure 6.5. Nevertheless, neglecting uncertainties in LCIA leads to a systematic underestimation of potential environmental impacts.

According to a common rule of thumb [107], a difference in results between two BS configurations can be considered significant if their IQRs do not overlap. Under this criterion, the difference in production impacts between macro and micro configurations is significant in Figure 6.5. However, no significant difference in production impacts can be concluded between the macro 4G-LTE BSs. The same observation applies to total life-cycle impacts in Figure 6.6. Lastly, Figure 6.4 indicates that the marginal impact savings from increasing the use of recycled materials to produce BSs and from recycling components at EoL are not statistically significant. In contrast, the source of electricity supplying the BS appears to significantly affect its environmental impacts during the use stage.

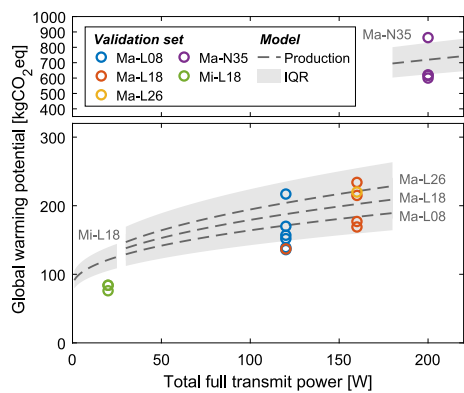


Fig. 6.8 Comparison of model predictions and validation data for the climate change impact of typical radio unit configurations during the production stage. Validation data generally falls within the inter-quartile range (IQR) of model predictions.

6.6 Model validation

As introduced in Section 4.5, model validation aims to qualitatively evaluate the accuracy of the proposed models. For the BS life-cycle model, validation involves comparing the predicted environmental impacts for specific BS configurations with corresponding empirical data from an independent validation set. This validation set should capture a representative diversity of BS configurations and must not have been used for model development or calibration. In practice, the validation set comprises environmental declarations made by manufacturers for 20 typical RUs. However, these declarations only cover the production stage, from cradle to gate, focusing on the GWP indicator. Therefore, only partial validation of the BS life-cycle model is possible. Furthermore, the validation data is not entirely independent of the model because the technical documentation was also used to derive the technological parameters. Yet, only data on material composition (e.g., aluminum mass) was used for FPI modeling. Thus, IAFs were calculated independently from GWP results reported by the manufacturers.

Figure 6.8 compares the GWP predicted by the BS life-cycle model with the corresponding data in the validation set for typical RU configurations. Here, the full transmit power per cell may vary for these configurations. The validation data generally falls within the IQR of model predictions, except for *Mi-L18*, whose production GWP appears slightly overestimated. Overall, Figure 6.8 demonstrates that the impact of RU production on climate change is modeled accurately.

6.7 Discussion

The life-cycle model developed in this chapter addresses the main research gaps identified in Chapter 3 regarding the environmental impact assessment of BSs. Specifically, the proposed model applies the ALCA methodology to assess entire BS life cycles across multiple environmental impact categories. This contrasts with previous LCA studies of BSs that primarily focused on GHG emissions from the production and use stages. To ensure consistency within the integrated RAN model, the life-cycle model directly employs the BS power model developed in Chapter 5 to quantify the electricity consumption during the use stage. Targeting multi-band BSs, the life-cycle model provides a consistent representation of different BS components, including traditional RUs and modern AAUs, across various configurations. Furthermore, the explicit distinction between FPI and IAFs enhances the flexibility of the model and facilitates adapting the background system without modifying the model structure. In addition, relying on specific empirical data sources improves the representativeness of the FPI and IAFs compared to previous studies that relied predominantly on generic background processes. Together, these elements enable the proposed life-cycle model to consistently assess and compare the environmental impacts of different commercial BS configurations throughout their life cycles.

The results obtained in this chapter confirm a key conclusion of previous LCA studies: the use stage dominates the GWP of BSs. This conclusion holds true with both the current average electricity grid mix in Europe and the autonomous PV system. However, the estimated GWP for producing one BS (1-4 tCO₂eq) lies at the lower end of the range reported in the literature (from 3 to > 30 tCO₂eq). These lower results are primarily explained by the focus on single-band BSs and by the restriction of system boundaries to communication-specific components, thereby excluding support components and site construction. While the latter choice limits the scope of the proposed model, it strengthens consistency within the integrated RAN model and enables detailed comparisons between BS designs. Beyond climate change, the use stage dominates across impact categories, highlighting the central role of the electricity supply in mitigating the environmental footprint of BSs. The multi-indicator assessment also reveals that the production stage is a hotspot for mineral and metal resource use, especially in microcell BSs. Yet, none of the previous LCA studies of BSs assesses all impact categories of EF 3.1, preventing comprehensive benchmarking of the results across categories.

Nevertheless, several limitations affect the technological, geographical, and temporal representativeness of the proposed life-cycle model. First, the empirical dataset used for model calibration does not capture the full variability of the foreground and background systems over time, across manufacturers, and between technologies. The limited availability of information and empirical data for modern BS designs (e.g., small-cell BSs and mmWave systems) also necessitates limit-

ing the scope of the model. Second, the modeling of the final component assembly, BS installation and deinstallation, and component disassembly through electricity consumption alone requires further validation, even if impacts of these processes appear negligible under this assumption. Third, the IAF calculations rely on a small number of teardowns, leading to the consideration of a static background system while it would actually vary depending on factors such as the manufacturing year or location. Finally, the ecoinvent database used to model the background system lacks the sufficient geographical and technological granularity for certain background processes. As a result, IAF calculations rely predominantly on the global average unit processes of ecoinvent and necessitate the development of custom unit processes for specific electronic elements.

Additional limitations stem from methodological choices and from the structure of the model. First, the BS components are assumed to be perfectly sized with respect to the model variables, especially the number of cells. In practice, however, the BS components may be intentionally oversized, e.g., to accommodate future BS upgrades. Second, the cut-off approach strongly favors the use of recycled materials in production but does not account for avoided impacts at the EoL, thereby limiting incentives for recycling [236]. Moreover, the 100:0 ratio for allocating the recycling burdens benefits systems that produce recyclable waste but disadvantages systems that use the recycled materials. Thus, applying alternative allocation ratios ranging from 80:20 to 20:80 could be more balanced, as recommended by the EU [208], although their implementation using ecoinvent remains challenging. Third, an optional mix of raw materials consisting of higher recycled content is considered only for aluminum at the production stage, though other materials could also benefit from such a specific mix (e.g., electronics and polymers). However, modeling these specific raw material mixes would require a more detailed knowledge of waste management routes and the availability of associated processes in ecoinvent. Similar constraints explain why EoL modeling remains relatively streamlined in the proposed life-cycle model.

Despite these limitations, the relatively low complexity of the proposed life-cycle model is a deliberate design choice intended to ensure usability, flexibility, and interpretability. These characteristics are particularly relevant for future research involving the evaluation of different BS configurations. The technological parameter estimates are also intended to be updated as new empirical data becomes available, without requiring a modification to the general model structure. This flexibility is important for reflecting the evolution of BS designs and of the technosphere. It also enables the exploration of BS configurations that extend beyond the initial scope of the model. Additionally, the multi-indicator perspective of the model allows for examining potential burden shifting and identifying BS design trade-offs. Furthermore, users of the model are encouraged to perform uncertainty and sensitivity analyses based on the uncertainty quantification presented in this chapter. Although this aspect tends to be overlooked in the literature, it is essential

to prevent overinterpreting the results and marginal differences between configurations. Overall, the proposed BS life-cycle model establishes a realistic baseline and structured assessment framework for future works targeting BS development. These developments are especially important for mitigating the impacts of BSs on climate change and resource use, as these categories significantly contribute to the weighted LCIA results. However, the relative perspective of LCA remains insufficient to determine whether a given BS configuration achieves absolute environmental sustainability, as further discussed in Chapter 8.

Summary

This chapter develops a parametric model of BS life-cycle environmental impacts designed for use within the integrated RAN model. Following the LCA methodology, the model assesses environmental impacts across multiple indicators and covers all life-cycle stages, from production to distribution, use, and EoL. The production stage is modeled by aggregating the impacts of producing physical BS components, including the BBU, RUs, AUs, PSU, and external cables. The use stage is directly modeled by the BS power consumption model. Foreground process quantities of the model are estimated using BS component teardowns and technical documentation from equipment manufacturers. The corresponding background impact factors are calculated using the ecoinvent database. Applying the life-cycle model to typical BS configurations shows that the use stage dominates all impact categories. The production stage may also have significant impacts, particularly regarding mineral and metal resource use. Conversely, the distribution and EoL stages are generally negligible. Therefore, the key levers for mitigating the BS environmental impacts are reducing their energy consumption and opting for low-impact electricity sources. In contrast, increasing the use of recycled materials in production and recycling components at EoL only marginally reduce life-cycle impacts. The GWP of producing macrocell BSs is estimated at 1-2 tCO₂eq per traditional band and 4 tCO₂eq when using massive-MIMO, whereas it represents around 0.3 tCO₂eq for a microcell BS. Model uncertainty is quantified as $\pm 15\%$, and model validation demonstrates a good prediction accuracy for the GWP of RU production.

PART II

**Application of the
integrated network model
toward environmental
sustainability**

7

Efficient base station designs under typical operating conditions

This second part of the thesis applies the integrated RAN model developed in Part I to address additional research gaps identified in Chapter 3. Focusing on research gaps related to efficient BS designs, this chapter addresses **RQ2** "*What BS designs are efficient in terms of QoS and direct environmental impacts under typical operating conditions?*" Specifically, it evaluates BS designs and operating conditions representative of RANs in Belgium. The examined BS designs are based on predetermined frequency band configurations (defined by frequency carrier, bandwidth, transmit power, etc.), and the operating conditions capture both the network configuration (e.g., BS density and radio propagation environment) and network usage (e.g., UE density and data traffic volume per UE). This chapter thus investigates how combinations of frequency bands affect the QoS, energy consumption, and environmental impacts of BSs, identifying the design trade-offs. It also analyzes the energy-saving potential of different PSSs. However, since the network usage is treated as an exogenous variable with respect to the provided QoS, this chapter does not capture rebound mechanisms and associated rebound effects.

The structure of this chapter is as follows. First, Section 7.1 defines general use cases, including frequency band configurations and typical operating conditions, which serve as the basis for subsequent BS evaluations. Then, Section 7.2 analyzes the effects of different PSSs on the QoS and power consumption for specific BS configurations under urban operating conditions, and discusses the relevance of each strategy. Building on this analysis, Section 7.3 evaluates additional BS configurations supporting one or more frequency bands in 4G-LTE and 5G-NR across rural, urban, and dense urban operating conditions. These evaluations cover QoS, energy

consumption, and environmental impacts of the production stage, highlighting key design trade-offs. The section also derives energy intensity metrics under different normalization perspectives. Since this chapter does not include uncertainty analysis, differences in results $< 10\%$ should not be interpreted as statistically significant. Finally, Section 7.4 discusses the main findings of the chapter in light of the state of the art, identifies its limitations, and outlines perspectives for future works. The content of this chapter has not yet been published elsewhere.

7.1 General use cases

In this chapter, BS evaluations are based on the general use cases defined in this section. First, it presents the configurations of frequency bands examined in the following sections. Then, it explains the principles of examined PSSs. Lastly, it describes the general operating conditions that apply throughout the chapter.

7.1.1 Frequency band configurations

The configuration of a BS is primarily determined by its frequency bands. In this chapter, the examined BSs can support one or more of the six frequency band configurations defined in Table 7.1. These configurations are representative of the frequency bands deployed in Belgium, in line with the typical BS configurations determined in Section 4.5. Table 7.1 specifically defines the frequency bands in terms of the BS configuration variables used in the integrated RAN model. Note that the table only lists the variables that differ between frequency bands, while the default values in Table 4.1 apply to the other variables.

The first five frequency bands correspond to macrocell BSs, and the last band, *Mi-L18*, corresponds to a microcell BS. All macrocell configurations have three sectors with directional antennas, whereas the microcell configuration supports a single cell with an omnidirectional antenna. Three of the macrocell configurations operate with the 4G-LTE protocol in FDD – *Ma-L08*, *Ma-L18*, and *Ma-L26* – with bandwidths of 10, 20, and 20 MHz at frequencies of 0.8, 1.8, and 2.6 GHz, respectively. The microcell configuration also uses 4G-LTE in FDD with a 20 MHz bandwidth at 1.8 GHz. All of these configurations employ RRUs, except *Ma-L08* that employs RFUs. These RUs embeds 2 or 4 TRXs, transmitting 80 W per cell for macrocell configurations and 10 W per cell for the microcell configuration. Moreover, two macrocell configurations operate with the 5G-NR protocol – *Ma-N07* and *Ma-N35* – with bandwidths of 10 MHz in FDD and 100 MHz in TDD at frequencies of 0.7 and 3.5 GHz, respectively. Similar to *Ma-L08*, *Ma-N07* employs RFUs, embedding 2 TRXs with an 80 W transmit power per cell. The more recent *Ma-N35* configuration employs AAUs implementing ABF with 8 spatial data layers and 64 TRXs, and a total transmit power of 200 W per cell. Since the output power per PA is lower in

Ma-N35 and *Mi-L18*, their PA architecture is Class-AB, while the other configurations implement the Doherty architecture.

In 4G-LTE RANs, *Ma-L08* is typically the coverage band, while *Ma-L18* and *Ma-L26* are the capacity bands. Similarly, *Ma-N07* is typically the coverage band in 5G-NR RANs, while *Ma-N35* is the capacity band. Furthermore, microcell configurations like *Mi-L18* are generally deployed in areas with heavy data traffic, such as sports stadiums, as well as in challenging coverage areas, such as subway stations. The total resource capacity of a BS configuration is expressed in MHz and is calculated by summing the capacity of its individual cells as

$$C_{BS} = N_S \sum_{i=1}^{N_B} N_{L,i} B_i \cdot (\tau_{DL,i} + \tau_{UL,i}), \quad (7.1)$$

where N_S and N_B are respectively the number of sectors and frequency bands, $N_{L,i}$ is the number of spatial data layers of band i , and B_i is the bandwidth of band i . Additionally, $\tau_{DL,i} + \tau_{UL,i}$ represents the duplex scheme for band i , since $\tau_{DL} = \tau_{UL} = 1$ in FDD, and $\tau_{DL} + \tau_{UL} = 1$ in TDD.

7.1.2 Power saving strategies

Static power consumption typically accounts for a significant portion of BS energy consumption, especially at low average data traffic loads. Therefore, PSSs aim to reduce this static power by adapting the active BS configuration over time in accordance to the load [43–46]. For instance, PSSs can activate or deactivate certain physical resources of the BS in the time, frequency, or spatial domains. In turn, the associated BS components and subcomponents can be switched to sleep mode, which consumes less power. These adaptations can occur at two time scales: fixed PSSs on an hourly basis or dynamic PSSs on a multi-frame basis (typically every 20 ms). The five PSSs examined in this chapter are presented in Table 7.2 in terms of the associated BS configuration variables in the integrated RAN model.

The first two PSSs are fixed and adapt the active BS configuration to the hourly average resource load. The fixed band sleep strategy, *fBS*, implements a frequency-domain PSS that deactivates entire frequency bands below certain resource load thresholds. This PSS is only effective for multi-band BSs, as at least one band must remain active to provide minimal service availability. Then, the fixed layer sleep strategy, *fLS*, combines frequency- and spatial-domain PSSs, activating physical resources in groups of spatial data layers within each frequency band. These groups may comprise 2^l spatial layers with $l \in \{1, 2, 3, \dots\}$, such that a band supporting, e.g., 8 layers can activate 2, 4 or 8 layers, or be fully deactivated. Thus, *fLS* is effective for multi-band BSs, as well as single-band BSs with ≥ 4 layers, ensuring that at least one group of spatial layers remains active to provide minimal service availability. For both *fBS* and *fLS*, the same activation threshold of 0.2 is used for all resource activation steps. This means that additional resources (either spatial

Table 7.1 Frequency band configurations

Variable	Ma-L08	Ma-L18	Ma-L26	Ma-N07	Ma-N35	Mi-L18
h_{BS} [m]	25	25	25	25	25	10
N_S [#]	3	3	3	3	3	1
κ_{prot}	4G-LTE	4G-LTE	4G-LTE	5G-NR	5G-NR	4G-LTE
κ_{duplex}	FDD	FDD	FDD	FDD	TDD	FDD
f [GHz]	0.8	1.8	2.6	0.7	3.5	1.8
B [MHz]	10	20	20	10	100	20
N_L [#]	2	2	4	2	8	2
N_{TRX} [#]	2	2	4	2	64	2
P_{TX}^{max} [W]	40	40	20	40	3.125	5
P_{TX}^{full} [W]	40	40	20	40	3.125	5
ψ_{hHPBW} [°]	65	65	65	65	90	—
G_{TX}^{max} [dBi]	16	16	16	16	23	0
κ_{ABF}	without	without	without	without	with	without
δ_{cable} [/]	0	0.8	0.8	0	1	1
κ_{RU}	RFU	RRU	RRU	RFU	AAU	RRU
$\kappa_{PA,arch}$	Doherty	Doherty	Doherty	Doherty	Class-AB	Class-AB
$\kappa_{PA,tech}$	LDMOS	LDMOS	LDMOS	LDMOS	GaN	GaAs

Table 7.2 Power saving strategies

Variable	fBS	fLS	dBS	dLS	dtx
κ_{fPSS}	band sleep	layer sleep	no	no	-
$\bar{x}_{fPSS}$	0.2	0.2	-	-	-
κ_{dPSS}	no	no	band sleep	layer sleep	-
$\bar{x}_{dPSS}$	-	-	0.3	0.3	-
δ_{PA}^{dtx}	1	1	1	1	0.25

Table 7.3 Adjusted technological parameters of power saving strategies

Parameter	Default	Adjusted
δ_{phy}^{sleep}	0.75	0.25
δ_{proc}^{sleep}	0.75	0.25
δ_{TRX}^{sleep}	0.50	0.25
δ_{TRX}^{idle}	1.00	0.75

Table 7.4 User equipment configurations

Variable	Category A	Category B
$N_{RX,UE}$ [#]	2	4

layer groups or frequency bands) are activated for an hour in order to maintain the average active resource load $< 20\%$. Yet, once the BS is fully active, the average resource load may exceed the threshold up to full load and saturation.

The next two PSSs are dynamic and adapt the active BS configuration to the average resource load over 20 ms intervals. These two PSSs actually reproduce the two fixed PSSs in the short term: the dynamic band sleep, dBS , corresponds to fBS , and the dynamic layer sleep, dLS , corresponds to fLS . The only difference between the two types of PSS is the activation threshold, which is set at 0.3 for dynamic PSSs instead of 0.2. The last PSS, dtx , exploits DTX periods (i.e., active but unloaded symbols with no reference signal) to switch PAs from the active mode to a low-power operating mode. In this mode, a PA consumes $P_{PA}(0)\delta_{PA}^{dtx} < P_{PA}(0)$, where $P_{PA}(P_{TX})$ is the power consumption of a fully active PA when transmitting a power P_{TX} , and δ_{PA}^{dtx} is the associated power consumption fraction. For this time-domain PSS, Table 7.2 sets $\delta_{PA}^{dtx} = 0.25$, which equates to a 75% power saving in PAs when they are not transmitting a signal over an active symbol.

Furthermore, the values of certain technological parameters are adjusted in the integrated RAN model to accentuate the effects of PSSs on BS power consumption, compared to using the default estimates for commercial BSs (see Part I). These parameters are the power consumption fractions for physical layer processors in sleep mode, front end processors in sleep mode, and TRXs in idle and sleep modes. The default and adjusted values for these parameters are provided in Table 7.3.

7.1.3 Operating conditions

The operating conditions for BS evaluations are defined by configuration variables related to the network (e.g., BS density), the UEs (e.g., number of receive antennas), and the radio channel (e.g., propagation environment). Evaluations generally use the default values for these variables unless specified otherwise for specific use cases. In all cases, only two UE categories are considered: *Category A* and *Category B* with 2 and 4 receive antennas, respectively (see Table 7.4).

Operating conditions also depend on network usage, which is specified by the hourly data traffic volume per UE as input variable of the integrated RAN model. The typical data traffic profile used in this chapter is depicted in Figure 7.1 over a one-day period, based on [JP1]. This profile indicates peak hours at noon and off-peak hours at night, with a $\times 7.5$ amplitude. Defining V_{UE} as the total data traffic volume per UE per day, the corresponding data traffic volume during hour t_h is

$$\bar{v}_{UE}[t_h] = \frac{V_{UE}}{24} \bar{v}_{profile}[t_h], \quad (7.2)$$

where $\bar{v}_{profile}[t_h]$ is the normalized hourly data traffic profile. As discussed in Appendix A.2, 90% of this data traffic volume occurs in the DL.

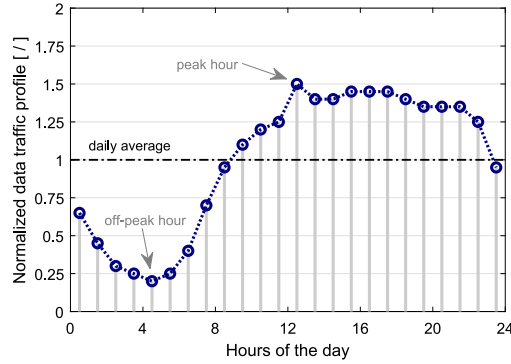


Fig. 7.1 Hourly data traffic profile over one day, normalized with respect to the daily average. Peak hours are at noon, and off-peak hours are at night (adapted from [JP1]).

7.2 Power saving strategy analysis

Before evaluating BSs under typical operating conditions, this section analyzes the effects of PSSs on QoS and power consumption. First, it describes the specific BS configurations and operating conditions that are investigated. Then, it analyzes the band sleep strategies. Lastly, it analyzes the layer sleep strategies.

7.2.1 Specific use cases

The PSS analysis involves the set of specific macrocell BS configurations listed in Table 7.5. These configurations support up to the three 4G-LTE frequency bands defined in Table 7.1. The first three configurations – *1L*, *2L*, and *3L* – support one to three frequency bands and serve as the baseline for the analysis because they do not implement PSSs. The next three configurations apply the band sleep strategies to *3L*, including *fBS* only, *dBS* only, and *dBS+dtx*. Similarly, the last three configurations apply the layer sleep strategies to *3L*, including *fLS* only, *dLS* only, and *dLS+dtx*. These PSSs refer to those defined in Table 7.3.

The operating conditions for these BSs are specified in Table 7.6 for a single *Urban* deployment area, based on the corresponding area identified in [JP1]. This deployment area is characterized by a BS density of one BS per 3 km² and a population density of 750 pers/km². Assuming three identical MNOs with equal market shares, this yields a UE density of 250 UE/km², or 750 UEs per BS. In this analysis, 100% of UEs are assumed to be *Category B* with 4 receive antennas. This optimistic assumption aims to accentuate the effects of PSSs, even though a more realistic assumption would be roughly 80% *Category A* and 20% *Category B* (see Appendix A.4). Finally, the average data traffic volume demand is set at 600 MB/UE/day, as in Europe in 2023 [247].

Table 7.5 Specific base station configurations for power saving strategy analysis

Configuration	3L (band sleep)						3L (layer sleep)		
	1L	2L	3L	fBS	dBS	+dtx	fLS	dLS	+dtx
Frequency bands									
Ma-L08	x	x	x	x	x	x	x	x	x
Ma-L18		x	x	x	x	x	x	x	x
Ma-L26			x	x	x	x	x	x	x
Power saving strategies									
fBS				x					
fLS							x		
dBS				x			x		
dLS							x		
dtx							x		

Table 7.6 Specific operating conditions for power saving strategy analysis

Variable	Urban
κ_{envi}	suburban
ρ_{BS} [BS/km ²]	0.33
ρ_{UE} [UE/km ²]	750/3
$\delta_{UE,A} \delta_{UE,B}$ [/]	0 1
V_{UE} [MB/UE/day]	600

7.2.2 Band sleep strategies

The analysis of fixed and dynamic band sleep strategies is based on the models shown in Figure 7.2 as functions of the hourly data traffic volume per UE. Figure 7.2(a) examines the models for the average active resource load, Figure 7.2(b) those for the average resource availability (i.e., the average ratio of active physical resources), Figure 7.2(c) for the average DL throughput per UE (which is a key QoS metric), and Figure 7.2(d) for the average power consumption per BS.

As a starting point, it is useful to examine the BS configurations without PSSs (i.e., 1L, 2L, and 3L). In Figure 7.2(a), the increase in average resource load for these BSs is convex with the data traffic volume. This convexity is explained by the increase in inter-cell interference as the average network load increases, which degrades the SINR at high loads. Consequently, the average SE also degrades with the load, slowing down the marginal growth of data traffic volume per unit of physical resource. Figure 7.2(a) also shows that the three BSs without PSSs reach full load at around 25, 70, and 125 MB/UE/h in the *Urban* area, reflecting the differing BS capacities (particularly in terms of total bandwidth). The full availability of physical resources for these BSs is confirmed by Figure 7.2(b). Then, Figure 7.2(c)

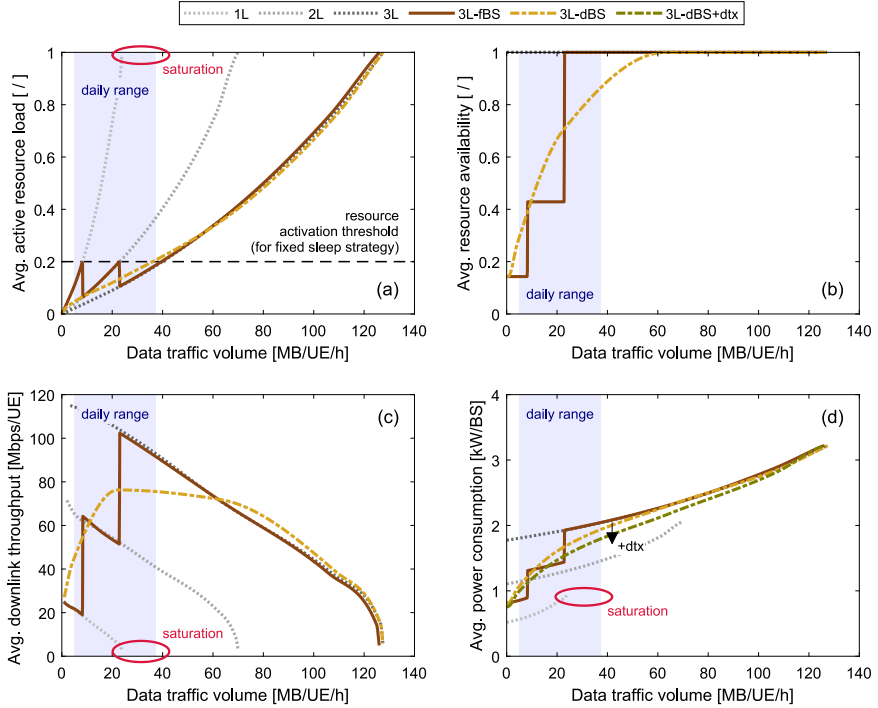


Fig. 7.2 Models as functions of the hourly data traffic volume per user equipment for base stations with band sleep strategies: (a) average load of active physical resources, (b) average physical resource availability, (c) average downlink throughput per user equipment, and (d) average power consumption per base station. Shaded areas indicate the daily range of hourly data traffic for a daily data volume of $V_{UE} = 600$ MB/UE/day.

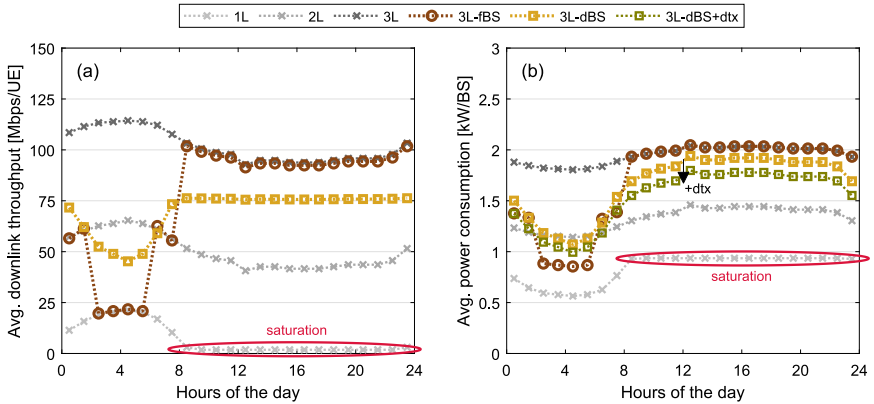


Fig. 7.3 Hourly profiles over one day for base stations with band sleep strategies: (a) average downlink throughput per user equipment, and (b) average power consumption per base station. *dBS* outperforms *fBS* in both throughput stability and energy savings.

shows that the increase in data traffic volume causes a steady decline in the average DL throughput per UE. It also illustrates that BSs with greater capacity offer higher data throughput, up to 25, 70, and 115 Mbps/UE for the *1L*, *2L*, and *3L* configurations, respectively. Lastly, Figure 7.2(d) shows that the average power consumption of these BSs is dominated by static power, respectively 520, 1105, and 1775 W, reflecting their number of frequency bands. The power consumption of these BS also goes upward with increasing data traffic volume, reaching respectively 930, 2060 and 3215 W at full load.

Based on this initial analysis, the fixed and dynamic band sleep strategies can be studied for the *3L* configuration. Figure 7.2(a) illustrates how physical resources are activated for these strategies. For the fixed strategy (see *3L-fBS*), only the *Ma-L08* band is activated in one-hour periods of low average load until 20% of this band is occupied. Once this threshold is crossed, the *Ma-L18* band is also activated, causing the average load on active resources to drop to 8%. In turn, when the average load on these two bands reaches 20% again, the last *Ma-L26* band is activated, causing the average load to drop to 10%. The average resource load of *3L-fBS* then follows the curve for *3L* up to full load. This shows that the model for *3L-fBS* successively follows the models for the three BSs without PSSs. The two steps of physical resource activation are also clearly visible in Figure 7.2(b). At low loads, 14% of the BS capacity is activated (i.e., *Ma-L08* only), 43% between 8 and 23 MB/UE/h (i.e., with *Ma-L08* and *Ma-L18*), and 100% at higher data traffic loads. The dynamic version of the band sleep strategy (see *3L-dBS*) produces smoother hourly models and eliminates slope discontinuities. As the *dtx* strategy has no effect on resource availability, the curves for *3L-dBS+dtx* are not shown in Figures 7.2(a) and 7.2(b).

The effects of band sleep strategies on QoS are examined in Figure 7.2(c) in terms of average DL throughput per UE. As in Figures 7.2(a) and 7.2(b), the QoS of *3L-fBS* jumps from *1L*, *2L*, and *3L* curves, depending on the number of active bands. As a result, QoS is limited to around 20 Mbps/UE during low-load hours, then rises to around 60 Mbps/UE during hours with data traffic between 8 and 23 MB/UE/h, and reaches around 100 Mbps/UE when all bands are active. With a continued increase in data traffic, the throughput then declines to zero at around 125 MB/UE/h, as for *3L*. Once again, the dynamic strategy smooths the QoS curve by eliminating abrupt transitions due to band activation from hour to hour. Moreover, it creates a plateau around 75 Mbps/UE for data traffic ranging from 20 to 70 MB/UE/h. Next, Figure 7.2(d) illustrates the incremental power consumption increase of *3L-fBS* with the successive band activation. The first and second power levels are higher than the corresponding power consumption of *1L* and *2L* because components in sleep mode still consume a non-zero amount of power. The DBB static power is also greater, as *3L* supports more cells than *1L* and *2L*. As before, the power model for *3L-dBS* is a smoothed version of that for *3L-fBS*. For both *3L-fBS* and *3L-dBS*, the static power at no load is 810 W, representing a 55% power saving compared to *3L*. Implementing the *dtx* strategy results in an additional 10% power

saving for traffic loads $< 50\%$. Beyond, the dtx savings diminish and vanish at full load, when there are no more DTX opportunities.

To analyze the effects of band sleep strategies over the course of one day, the hourly models can be applied to hourly data traffic profiles. Figure 7.3 applies the models of average throughput per UE and power consumption per BS to the data traffic profile shown in Figure 7.1 with $V_{UE} = 600$ MB/UE/day. The corresponding daily range of hourly data traffic volume per UE is depicted in Figure 7.2.

For BSs without PSSs, Figure 7.3(a) shows that the average throughput per UE varies in the opposite direction of the data traffic profile: the QoS is high during off-peak hours and low during peak hours. Under *Urban* operating conditions, *1L* even experiences saturation most of the day (from 9 a.m. to 11 p.m.) due to insufficient capacity. With *fBS*, the average throughput varies $\times 5$ between the least loaded hour of the night (when only one band is active) and the least loaded hour of the day (when all three bands are active). The dynamic strategy enables *3L-dBS* to reduce the throughput discrepancy to a $\times 1.7$ factor between the lowest and highest hours of the day. Additionally, it allows for better throughput consistency, with a plateau around 75 Mbps/UE during the day. The peak throughput of *3L-dBS* is $\times 3/4$ that of *3L-fBS* during the day, but $\times 2$ that of *3L-fBS* at night. Then, Figure 7.3(b) shows how band sleep strategies affect BS power consumption. Power savings are mainly achieved during off-peak hours at night. Over a full day, *fBS* and *dBS* achieve 12% and 15% energy savings, respectively, and *dBS+dtx* even reaches 21% savings. Therefore, the dynamic strategy is superior to the fixed strategy in terms of daily energy consumption, and provides more stable QoS throughout the day at the cost of a slight loss in peak data throughput.

7.2.3 Layer sleep strategies

Similar to band sleep strategies, the analysis of fixed and dynamic layer sleep strategies is based on the models shown in Figure 7.4 as functions of the hourly data traffic volume per UE. Figure 7.4(a) examines the models for the average active resource load, Figure 7.4(b) those for the average resource availability, Figure 7.4(c) for the average DL throughput per UE, and Figure 7.4(d) for the average power consumption per BS. The models for BSs without PSSs (i.e., *1L*, *2L*, and *3L*) are also depicted in Figure 7.4 as reference (see their analysis in Section 7.2.2).

The hourly models for BSs implementing layer sleep strategies are similar to those with band sleep strategies. Figure 7.4(a) shows that the main difference between *fLS* and *fBS* consists in the extra activation step at 37 MB/UE/h. In Figure 7.4(b), this results in an additional intermediate level of active resources at 71% of BS capacity, between 23 and 37 MB/UE/h. This level corresponds to the activation of 2 out of 4 spatial data layers of *Ma-L26*. In Figure 7.4(c), this additional level provides an average throughput per UE that is slightly lower than that provided by *3L*, reducing the peak throughput of *3L-fLS* to 95 Mbps/UE (compared to

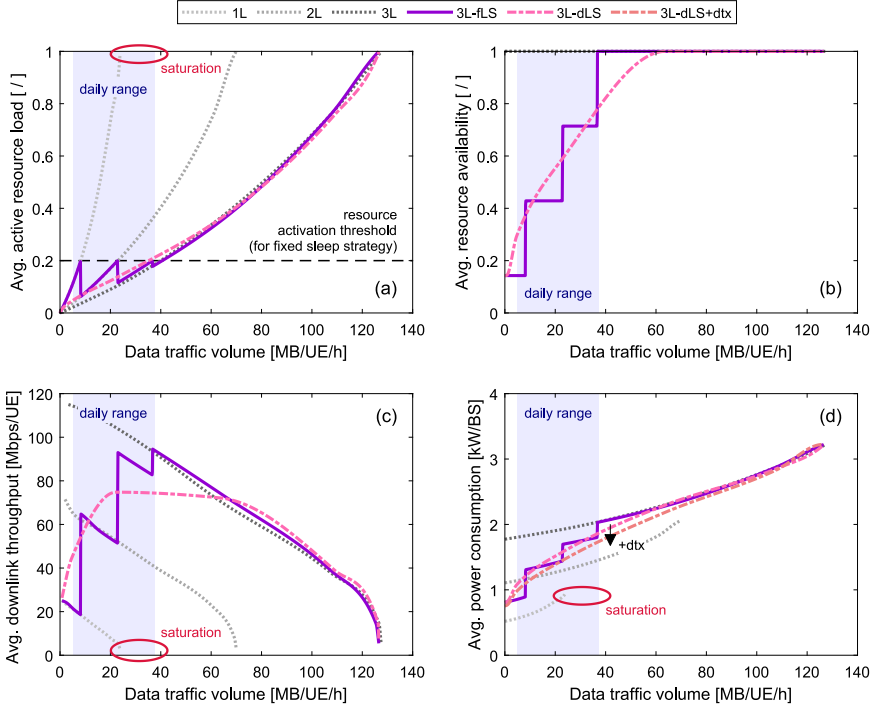


Fig. 7.4 Models as functions of the hourly data traffic volume per user equipment for base stations with layer sleep strategies: (a) average load of active physical resources, (b) average physical resource availability, (c) average downlink throughput per user equipment, and (d) average power consumption per base station. Shaded areas indicate the daily range of hourly data traffic for a daily data volume of $V_{UE} = 600$ MB/UE/day.

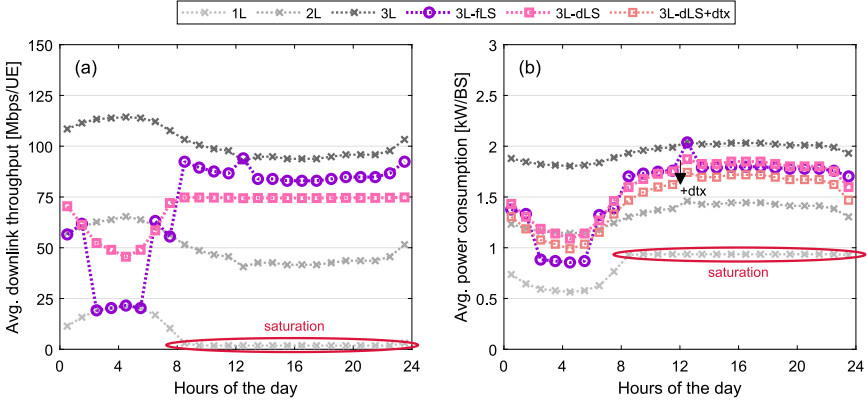


Fig. 7.5 Hourly profiles over one day for base stations with layer sleep strategies: (a) average downlink throughput per user equipment, and (b) average power consumption per base station. *dLS* provides more stable throughput but similar energy savings than *fLS*.

100 Mbps/UE for $3L$ -fBS). Lastly, Figure 7.4(d) shows that the additional activation step yields an extra intermediate power consumption level. This provides additional power savings by delaying the data traffic level at which all BS components become fully active. As in Figure 7.2, Figure 7.4 shows that dLS smooths the fLS models, causing $3L$ - dLS to closely resemble $3L$ - dBS . As with dBS , implementing the dtx strategy in addition to dLS results in an additional 10% power saving for traffic loads $< 50\%$. Beyond, the dtx savings diminish and vanish at full load, when there are no more DTX opportunities.

Note that the substantial difference in data throughput between 2 and 4 active spatial data layers in Ma -L26 is mainly due to the operating conditions that assume all UEs are equipped with 4 receive antennas. In 2023, however, most UEs were equipped with only 2 receive antennas instead of 4 in Belgium (see Appendix A.4). In that case, activating 4 layers instead of 2 means switching from 2×2 MIMO to 4×2 MIMO instead of 4×4 MIMO, which limits spatial multiplexing capabilities. Therefore, under realistic operating conditions, the difference in data throughput following the last activation step is less noticeable than shown in Figure 7.2(c).

The effects of layer sleep strategies over the course of one day are analyzed in Figure 7.5 by applying the models of average throughput per UE and power consumption per BS to the data traffic profile shown in Figure 7.1 with $V_{UE} = 600$ MB/UE/day. The corresponding daily range of hourly data traffic volume per UE is depicted in Figure 7.4.

Over the day, Figure 7.5(a) shows that layer sleep strategies offer a similar QoS as band sleep strategies. The main difference emerges with fLS , which activates all physical resources of the BS only during the busiest hour of the day (i.e., at 12 p.m.). During other hours of the day, only 2 of the 4 spatial layers of Ma -L26 are active, providing a slightly lower throughput than $3L$. At night, during off-peak hours, one or both capacity bands may be deactivated. Moreover, there is no significant difference in average data throughput per UE between $3L$ - fLS and $3L$ -fBS (see Figure 7.3(a)). Then, Figure 7.5(b) shows that both dLS and fLS achieve power savings throughout the day compared to $3L$ (except for fLS at noon). Thus, the difference in power consumption between $3L$ - fLS and $3L$ - dLS is less significant than the difference between $3L$ -fBS and $3L$ - dBS (see Figure 7.3(b)). Over a full day, fLS and dLS achieve 20% and 18% energy savings, respectively, and $dBS+dtx$ reaches 24% savings. Therefore, the fixed layer sleep strategy slightly outperforms the dynamic one in terms of daily energy consumption, unlike with the band sleep strategies. However, the dynamic strategy provides more stable QoS throughout the day, albeit with a slight loss in peak data throughput.

7.2.4 Relevant use of the strategies

Under typical operating conditions, previous analyses show that dynamic PSSs are generally superior to fixed PSSs. In terms of QoS, dynamic PSSs offer a more stable

average DL throughput per UE over the course of a day, despite having slightly lower peak average throughput. In terms of energy consumption, dynamic PSSs achieve similar or better energy savings over a full day compared to fixed PSSs. However, the practical implementation of dynamic PSSs is potentially more complex than that of fixed PSSs. Thus, dynamic strategies should prioritize band activation over layer activation, as similar energy savings can be achieved with fewer activation steps. Nevertheless, layer sleep strategies remain relevant for fixed PSSs because they provide similar QoS as fixed band sleep strategies but with greater energy savings. Furthermore, strategies exploiting DTX are always relevant, but their energy savings potential is limited to PAs.

In practice, layer sleep strategies are only relevant when multiple spatial layers can be effectively exploited within a cell. This primarily applies to frequency bands featuring multi-user MIMO and ABF (e.g., *Ma-N35*), enabling the BS to form several spatially separated beams and reuse time-frequency resources at different locations within the cell. As a result, the total cell throughput increases without requiring UEs to support multiple receive antennas. However, the availability of multiple beams is only beneficial when several UEs are active simultaneously and can be spatially separated. Therefore, layer sleep strategies provide a means to adapt the number of active spatial layers and associated TRXs to the instantaneous number of active UEs. This enables energy savings by avoiding the operation of unnecessary TRXs when spatial multiplexing opportunities are limited. At the same time, deactivating spatial layers reduces the maximum achievable beamforming gain and spatial selectivity of the BS, which may degrade the BS coverage.

7.3 Base station design evaluation

This section evaluates different BS configurations under typical operating conditions in order to inform the design of efficient BS. First, it introduces the specific BS configurations and operating conditions under study, which aim to represent RANs in Belgium under low and high usage. Next, the section assesses the QoS, energy consumption, and environmental impacts of these BSs at both usage levels, but only in urban areas. The results of these assessments are then used to identify and discuss key BS design trade-offs. Finally, the section estimates different energy intensity metrics to evaluate BS efficiency at different usage levels and in different deployment areas. It also discusses how to use these metrics to calculate the RAN energy consumption at the country or region level.

7.3.1 Specific use cases

BS evaluation involves the set of specific BS configurations listed in Table 7.7. These configurations are representative of the BSs operating in Belgium in 2023. This set includes 14 macrocell and 1 microcell configurations. The macrocell BS configura-

Table 7.7 Specific base station configurations for base station evaluation

Configuration	1L	2L	3L	4LN			3LN			2N			1N		μ 1L
				-	f	d	-	f	d	-	f	d	-	d	
Frequency bands															
Ma-L08	x	x	x	x	x	x	x	x	x						
Ma-L18		x	x	x	x	x	x	x	x						
Ma-L26			x	x	x	x									
Ma-N07										x	x	x			
Ma-N35				x	x	x	x	x	x	x	x	x	x	x	
Mi-L18															x
Power saving strategies															
fBS					x			x			x				
dLS						x			x			x		x	
dtx						x			x			x		x	

Table 7.8 Specific operating conditions for base station evaluation

Variable		Rural	Urban	Dense urban
<i>All usage levels</i>				
κ_{envi}		rural	suburban	urban
ρ_{BS} [BS/km ²]	macro (micro)	0.05 (33)	0.33 (33)	2 (33)
$\delta_{UE,A} \mid \delta_{UE,B}$ [/]		0.8 0.2	0.8 0.2	0.8 0.2
<i>Low usage level</i>				
ρ_{UE} [UE/km ²]		50/3	750/3	10 ⁴ /3
V_{UE} [MB/UE/day]		200	200	200
<i>High usage level</i>				
ρ_{UE} [UE/km ²]		100/3	1500/3	2×10 ⁴ /3
V_{UE} [MB/UE/day]		2000	2000	2000

tions support the macro 4G-LTE and 5G-NR frequency bands defined in Table 7.1. The 1L, 2L, and 3L configurations support one, two, and three 4G-LTE bands, and the 1N and 2N configurations support one and two 5G-NR bands, including *Ma-N35* with ABF in 64T64R. The 3LN and 4LN configurations combine 3 and 4 bands in 4G-LTE and 5G-NR. Finally, the $\mu 1L$ configuration supports a single microcell in the *Mi-L18* band. The 1N, 2N, 3LN, and 4LN configurations are also evaluated with the fixed band sleep PSS, *fBS*, and with the dynamic layer sleep plus DTX-based PSSs, *dLS+dtx*. These PSSs are defined in Table 7.3.

The typical operating conditions for these BSs are specified in Table 7.6 for three deployment areas (based on [JP1]): *Rural*, *Urban*, and *Dense urban*. The *Urban* area

is the base case for BS evaluation in Sections 7.3.2 to 7.3.5, while Section 7.3.6 evaluates energy intensity metrics for the three deployment areas. These areas are characterized by an increasing density of macrocell BSs, but a constant and higher density of microcell BSs due to their lower transmit power. All operating conditions assume that 80% of UEs are *Category A* with 2 receive antennas, and the remaining 20% are *Category B* with 4 receive antennas. These conditions also assume three identical MNOs with an equal market share of 1/3 of the UEs each. In addition, two network usage levels are considered for each area: *low* usage and *high* usage. At the low usage level, the UE density in a given area corresponds to its population density, and the average daily data traffic volume is 200 MB/UE/day, similar to Belgium around 2023 [248]. Then, the high usage level assumes $\times 2$ the UE density and $\times 10$ the data traffic volume of the low usage level, yielding a $\times 20$ overall network usage. Both usage levels follow the data traffic profile shown in Figure 7.1.

7.3.2 Quality of service

Three key QoS metrics for the specific BS configurations are examined in Figure 7.6 for the two network usage levels in the *Urban* area. Figures 7.6(a)-(c) focus on the low usage level and Figures 7.6(d)-(f) focus on the high usage level. The first examined QoS metric is the hourly average DL data throughput per UE, shown in Figures 7.6(a) and 7.6(d). The second QoS metric is the average physical resource load, which reflects the probability of network congestion. This metric is shown in Figures 7.6(b) and 7.6(e), where the maximum QoS threshold is set at 0.7. Above this threshold, QoS is assumed to degrade noticeably due to excessive traffic congestion. The third QoS metric is the user-centric DL coverage, which is defined as the fraction of UEs experiencing adequate DL signal quality to receive data from the BS. This last metric is shown in Figures 7.6(c) and 7.6(f), where the minimum QoS threshold is set at 0.95. Note that each figure shows both the daily average (i.e., the average of hourly values over one day) and the daily range (i.e., the range between the lowest and highest hourly values) of the QoS metrics.

At the low usage level, most BS configurations are lightly loaded (< 0.1), except for *1L* that peaks at 0.4. Thus, without PSSs, the average data throughput per UE is directly related to the BS capacity (from 15 Mbps/UE for *1L* to 390 Mbps/UE for *4LN*) and remain stable throughout the day because BSs are far from saturation. However, implementing *fBS* drastically reduces the throughput of *4LN* and *3LN* (to around 40 Mbps/UE) because the activation thresholds are not crossed at low loads. This causes certain bands (e.g., *Ma-N35*) to always remain in sleep mode. For *2N*, *fBS* only activates *Ma-N35* during peak hours, while *Ma-N07* operates alone for the rest of the day. Consequently, the throughput per UE fluctuates greatly throughout the day, as reflected by a wide daily range. Compared to *fBS*, *dLS* enables a higher average throughput for *4LN* and *3LN* (up to 95 Mbps/UE) and improves the throughput consistency of *2N*, albeit with a slight decrease in the daily average throughput. When applied to *1N*, *dLS* activates only a subset of the

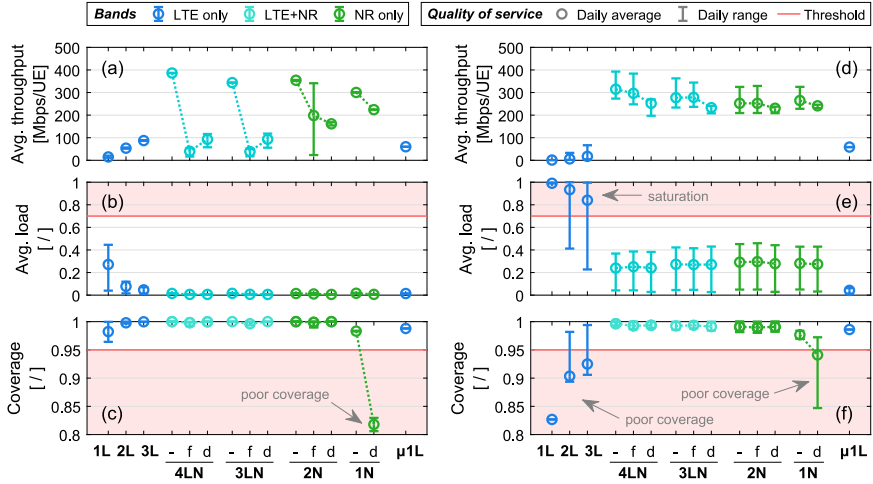


Fig. 7.6 Quality of service for specific base station configurations in the *Urban* deployment area, under low usage level: (a) average downlink throughput per user, (b) average physical resource load, and (c) downlink coverage, and high usage level: (d) average downlink throughput per user, (e) average physical resource load, and (f) downlink coverage. At low usage, most configurations are lightly loaded. At high usage, 4G-LTE-only configurations are saturated, resulting in poor coverage, while most others provide high throughput.

spatial data layers, reducing the beamforming gain and spatial selectivity of the BS. As a result, the average throughput decreases slightly and, more importantly, the coverage degrades well below the QoS threshold (to 0.82). All other configurations offer coverage that meets the QoS threshold.

At the high usage level, in contrast, 4G-LTE-only macrocell BSs are saturated most of the time, with average resource loads generally exceeding the QoS threshold. As a result, their average throughput per UE is significantly lower than at the low usage level. Network saturation also leads to strong and persistent inter-cell interference, which in turn degrades DL coverage below the QoS threshold. Poor coverage is particularly noticeable for *1N* (i.e., 0.83). With or without PSSs, the other macrocell BSs achieve an average load of 0.25-0.30, climbing up to 0.5 during the busiest hour. For these BSs, the daily average throughput per UE varies from 230 to 310 Mbps/UE, with a daily range of around 100 Mbps/UE. These results suggest that these BS configurations are well suited to the operating conditions. Compared to the low usage level, *fBS* no longer significantly affects throughput because all bands remain active most of the day. Meanwhile, *dLS* improves throughput consistency during the day but significantly degrades the coverage of *1N*, as at the low usage level. Finally, the QoS metrics for *μ1L* do not vary significantly between the two usage levels because this configuration remains very lightly loaded in both cases due to the $\times 100$ BS density compared to macrocell BSs.

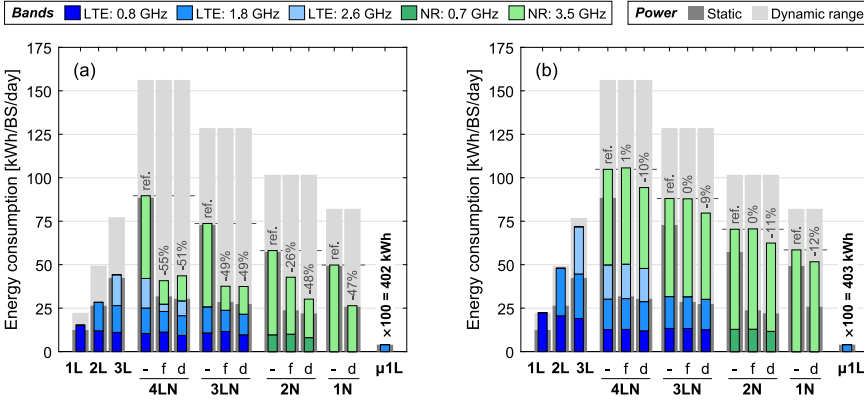


Fig. 7.7 Daily energy consumption of specific base station configurations in the *Urban* deployment area (a) under low usage level, and (b) under high usage level. Energy consumption is primarily driven by the number of installed frequency bands and the transmit power per band. At low usage, static power dominates energy consumption and can be reduced through power saving strategies. At high usage, only *dLS* achieves energy savings.

7.3.3 Energy consumption

The daily energy consumption of the specific BS configurations, broken down by frequency band, is examined in Figure 7.7 at both network usage levels in the *Urban* area. Figures 7.7(a) focuses on the low usage level, and Figures 7.7(b) focuses on the high usage level. These results per BS and per day can then be used to calculate energy efficiency or intensity metrics for the RAN (see Section 7.3.6).

At the low usage level, static power consumption accounts for a large part of the energy consumption of most BS configurations because they are all lightly loaded. Without PSSs, the BS energy consumption is primarily driven by the number of installed frequency bands and the transmit power per band. For instance, traditional macrocell bands (i.e., without ABF) consume 10-18 kWh/BS/day each, whereas *Ma-N35* consumes around 50 kWh/BS/day due to its higher total transmit power and numerous TRXs. Yet, implementing PSSs can significantly reduce the static power consumption of BSs. For instance, both *fBS* and *dLS* achieve about –50% in daily energy consumption of *4LN* and *3LN* by keeping *Ma-L26* and *Ma-N35* in sleep mode most of the time. For *2N* and *1N*, *dLS* also achieves around –50% energy consumption, while *fBS* achieves only –26% for *2N*. Thus, *dLS* outperforms *fBS* for BSs that primarily rely on massive-MIMO. Instead of the 15-90 kWh/BS/day consumed by macrocell BSs, *μ1L* consumes 4 kWh/BS/day only. However, ×100 microcell BSs are required to cover the same area as one macrocell BS, resulting in a comparable 402 kWh/day. Therefore, it is not relevant for RANs to operate exclusively with microcell BSs in *Urban* areas.

At the high usage level, in contrast, the part of energy consumption due to dy-

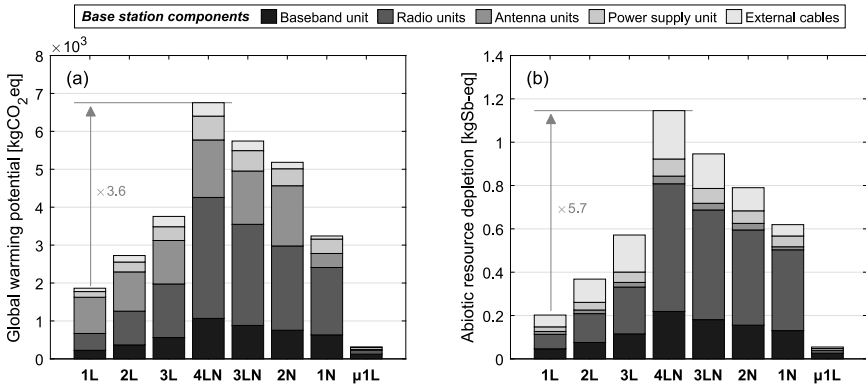


Fig. 7.8 Impacts of the production stage of specific base station configurations on (a) climate change, and (b) mineral and metal resource use. These impacts are primarily driven by the number of installed frequency bands and the number of transceivers per band. Radio units and antenna units dominates the global warming potential. Radio units dominates the abiotic resource depletion potential, with notable contributions from external cables.

namic power becomes significant and may even dominate for BS configurations with PSSs. In this case, traditional macrocell bands consume 12-27 kWh/BS/day each, and *Ma-N35* consumes up to 58 kWh/BS/day. Furthermore, *fBS* no longer offers any energy savings compared to BSs without PSSs because all frequency bands remain fully active throughout the day. Unlike *fBS*, *dLS* still achieves approximately –10% energy consumption by dynamically adapting the layer activation of *Ma-L26* and, especially, *Ma-N35*. At this usage level, macrocell BSs consume 22-105 kWh/BS/day, which is still well below the 403 kWh/day required to cover the same area with microcell BSs.

7.3.4 Environmental impacts

As shown in Chapter 6, most environmental impacts from the BS life cycle originate from electricity consumption during the use stage. Therefore, the BS energy consumption results shown in Figure 7.7 can be used to assess the largest part of BS life-cycle environmental impacts. For instance, GHG emissions from the BS use can be calculated based on the carbon intensity factor of the low-voltage electricity grid, which was 230 gCO₂/kWh in Belgium in 2019 [246]. Since the production stage is the second most impactful stage of the BS life cycle, Figure 7.8 shows environmental impact results for the specific BS configurations at the production stage only. These assessment results are broken down by BS components. Figure 7.8(a) focuses on GWP, and Figure 7.8(b) focuses on ADP.

The GWP of producing macrocell BSs ranges from 1.9 to 6.8 tCO₂eq. This ×3.6 range essentially reflects the number of frequency bands installed on the BS and the

number of TRXs per band. In traditional macrocell BSs without massive-MIMO (i.e., $1L$, $2L$, and $3L$), RUs and AUs equally dominate the production stage GWP, while for BSs with massive-MIMO RUs are the main contribution due to their large number of TRXs. Compared to macrocell BSs, the GWP of producing the microcell BS (i.e., $\mu 1L$) is much lower, at only 310 kgCO₂eq. Following similar trends, the ADP of the production stage ranges from 0.2 to 1.1 kgSb-eq for macrocell BSs and is 0.05 kgSb-eq for the microcell BS. With a $\times 5.7$ factor, the ADP range for macrocell BS production is greater than the corresponding GWP range. Furthermore, AUs no longer contribute significantly to ADP, unlike external cables that contribute more to ADP than to GWP, mainly due to the copper in power cables.

7.3.5 Design trade-offs

Designing BSs for eco-efficient RANs involves jointly studying the life-cycle environmental impacts and the QoS of BSs. Since the use stage largely dominates the BS environmental impacts, these impacts can be approximated by the BS energy consumption. A comprehensive QoS metric is also defined to summarize the key QoS aspects into a single performance indicator as

$$QoS = \begin{cases} \bar{r}_{UE} \cdot \left(\frac{\bar{x}_{QoS} - \bar{x}_{net}}{\bar{x}_{QoS}} \right) \cdot \left(\frac{\zeta_{net} - \zeta_{QoS}}{1 - \zeta_{QoS}} \right) & \text{if } \bar{x}_{net} < \bar{x}_{QoS} \text{ and } \zeta_{net} > \zeta_{QoS} \\ 0 & \text{if } \bar{x}_{net} \geq \bar{x}_{QoS} \text{ or } \zeta_{net} \leq \zeta_{QoS} \end{cases}, \quad (7.3)$$

where $\bar{r}_{UE}$ is the average throughput per UE, $\bar{x}_{net}$ is the average resource load, and ζ_{net} is the DL coverage. The average load is intended to capture the probability of traffic congestion, which increases as the load approaches full saturation. Additionally, $\bar{x}_{QoS}$ and ζ_{QoS} represent the QoS thresholds for the load and coverage, respectively. As in Section 7.3.2, these thresholds are set to $\bar{x}_{QoS} = 0.7$ and $\zeta_{QoS} = 0.95$. According to Equation (7.3), the comprehensive QoS metric corresponds to the average throughput per UE, adjusted linearly by the load and coverage relative to their respective QoS thresholds. Thus, when the load is low and the coverage is high, the QoS metric is close to the throughput per UE. Conversely, the QoS metric is zero when $\bar{x}_{net} \geq \bar{x}_{QoS}$ or $\zeta_{net} \leq \zeta_{QoS}$.

To support the evaluation of BS designs in the *Urban* area, Figure 7.9 plots the daily energy consumption against the daily average QoS metric for the specific BS configurations. For each configuration, the figure shows the trajectory from low to high usage levels via a gradual increase in the number of UEs and the data traffic volume per UE. Moreover, the figure only shows macrocell configurations because microcell BSs are not relevant in the *Urban* deployment area.

Without PSSs, the trajectories are fairly straight in the graph, going from a high to a low QoS and from a low to high energy consumption. The emerging trend reveals that both QoS and energy consumption increase with BS capacity. At the low

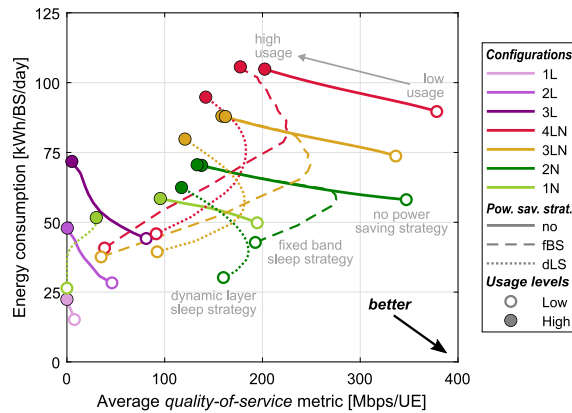


Fig. 7.9 Daily energy consumption per base station against daily average quality of service for specific base station configurations in the *Urban* deployment area. Trajectories progress from low to high usage levels and identify design trade-offs. Power saving strategies involves trade-offs between quality of service loss and energy savings. One of the best configuration is *2N*, combining a traditional coverage band with an advanced high-capacity band.

usage level, *fBS* deactivates part of the BS capacity to reduce its energy consumption at the expense of decreasing QoS. Then, as usage gradually increases, both QoS and energy consumption rise until all the BS capacity stay fully active throughout the day. Once this usage level is reached, the trajectory flips to align with the trajectory without PSS. In contrast, *dLS* achieves energy savings at all usage levels. It also improves QoS of *4LN* and *3LN* at low usage levels, while it degrades QoS of *2N* and *1N* at all usage levels. However, the daily average QoS does not reflect that using *dLS* offers a more stable QoS than *fBS* throughout the day.

Overall, *2N* appears to be one of the best configuration, combining a traditional low-frequency band with a more advanced high-frequency band featuring massive-MIMO and 8 spatial data layers. With this configuration, designing a PSS involves trade-offs between QoS loss and energy savings. This finding highlights the importance of balancing the number of installed frequency bands to maintain low energy consumption while preserving good QoS. It also emphasizes the benefits of combining a low-frequency band for coverage with a high-capacity band for high data throughput. Additionally, it shows that massive-MIMO with multiple spatial data layers offers the flexibility necessary for efficient PSSs.

7.3.6 Energy intensity metrics

To complete the BS design evaluation, energy intensity metrics (i.e., inverse energy efficiency) are calculated for the specific BS configurations across all operating conditions (i.e., low and high usage levels in *Rural*, *Urban*, and *Dense urban* deployment

areas). The four examined energy intensity metrics normalize the daily BS energy consumption based on the service provided (e.g., transmitting a certain data volume, connecting a certain number of subscribers, or covering a certain land area) or a technical characteristic (e.g., the physical resource capacity of the BS). These metrics can then be used to determine the best configurations for a given functionality. Specifically, Figure 7.10 shows the energy intensity metrics based on the data traffic volume in Figure 7.10(a), the number of UEs in Figure 7.10(b), the covered land area in Figure 7.10(c), and the BS capacity in Figure 7.10(d).

Across the operating conditions, the ranges of energy intensity metrics for the macrocell BS configurations are 0.01-1 kWh/GB, 0.006-0.3 kWh/UE/day, 0.7-300 kWh/km²/day, and 0.01-0.2 kWh/MHz/day. The conventional per-GB metric is sensitive to both aspects of operating conditions, varying approximately $\times 5$ between *Dense urban* and *Rural* areas and by an order of magnitude from the low to high usage level (see Figure 7.10(a)). In contrast, the per-UE and per-km² metrics are mostly sensitive to the deployment area while remaining roughly stable across usage levels (see Figures 7.10(b) and 7.10(c)). Furthermore, the per-GB perspective indicates that BSs are more efficient under high usage in dense areas, whereas the per-km² perspective suggests that BSs are more efficient at low usage in low-density areas. Lastly, the per-MHz metric appears to be the more stable across operating conditions (see Figure 7.10(d)). However, this metric reflects a technical characteristic of the BS (i.e., its capacity) rather than a useful service provided by the BS (e.g., transmitting data traffic). Therefore, service-oriented metrics (e.g., the SE in bps/Hz) must complement the per-MHz metric to account for the useful functions of BSs. Drawing a parallel with the LCA methodology (see Section 2.2.3), the per-MHz metric adopts a perspective closer to a reference flow, while the other three metrics adopt perspectives closer to FUs.

Given the operating conditions, the metrics remain within an order of magnitude for all macrocell BSs. Additionally, Figures 7.10(a)-(c) show that the ranking of macrocell BS configurations remains the same as in Figure 7.7. Accordingly, the most (resp. least) efficient configuration is *1L* (resp. *4LN*) because it consumes the least (resp. most) energy for an identical service provided. Yet, a notable difference appears with the per-GB metric in Figure 7.10(a) at the high usage level. In this case, the efficiency of 4G-LTE-only configurations (i.e., *1L*, *2L*, and *3L*) degrades due to saturation, which prevents the transmission of all data traffic. In contrast, the per-MHz metric yields a different ranking in Figure 7.10(d) because the consumed energy is normalized by a technical characteristic of the BS rather than by the service provided. In this case, *1L* and *1N* are the least and most efficient configurations, respectively. Interestingly, none of the configurations identified as the best through energy intensity metrics corresponds to the best design trade-off identified in Section 7.3.5 (i.e., *2N*). This illustrates that both relative and absolute evaluation perspectives are useful for informing BS design choices.

Regarding the microcell BS configuration (i.e., $\mu 1L$), the per-GB and per-UE en-

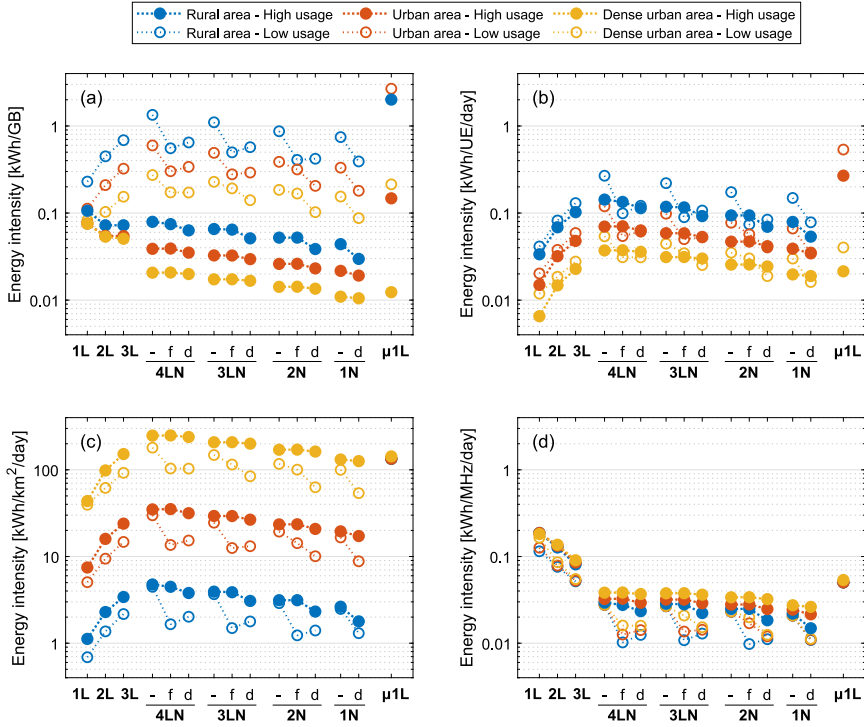


Fig. 7.10 Energy intensity metrics of the specific base station configurations under different operating conditions, in relation to (a) data traffic volume, (b) number of user equipment, (c) land area, and (d) base station capacity. The normalization perspective may influence the evaluation of base station efficiency. Intensity metrics per MHz (resp. per GB) are the most (resp. least) stable across operating conditions.

ergy intensity metrics are highly sensitive to operating conditions, ranging over 0.01-40 kWh/GB and 0.02-8 kWh/UE/day (see Figures 7.10(a) and 7.10(b)). Conversely, the limited dynamic power consumption and constant density of microcell BSs across deployment areas results in a stable per-km² metric across operating conditions, around 150 kWh/km²/day (see Figure 7.10(c)). Similarly, a stable per-MHz metric is obtained across operating conditions, around 0.05 kWh/MHz/day (see Figure 7.10(d)). Compared to macrocell BS configurations, the energy intensity metrics for the microcell BS configuration are similar only in the *Dense urban* area. However, these metrics are significantly worse in *Urban* and *Rural* areas for the microcell BS configuration, by up to two orders of magnitude. Therefore, deploying microcell BSs appears relevant only in *Dense urban* areas, where the macrocell RAN already has a high BS density.

Overall, this analysis of energy intensity metrics emphasizes the importance of

adapting the normalization perspective to the intended use of these relative performance indicators. For instance, the per-MHz metric is well-suited to first-order energy consumption assessments of RANs at the country level because it remains stable across deployment areas. Consequently, the total energy consumption can be obtained by multiplying this metric by the capacity per BS and the total number of BSs deployed in the country. However, if this approach is not possible due to unavailable data, intensity metrics per UE or per km² (ideally differentiated by deployment area) can be used instead. Conversely, the conventional per-GB metric should generally be avoided when scaling energy consumption at the country level because it is highly sensitive to operating conditions, as discussed in [JP2]. Examining other efficiency or intensity indicators may also be relevant when studying the functional, technical, or economic performance of RANs.

7.4 Discussion

The literature reviewed in Chapter 3 reveals historical improvements in the energy intensity of mobile networks. However, these aggregate trends do not identify which BS design choices contribute to such improvements under realistic network deployments and data traffic loads. To address this issue, this chapter applies the integrated RAN model developed in Part I to evaluate specific BS configurations under typical operating conditions. This evaluation aims to inform the design of efficient BSs in terms of QoS and direct environmental impacts, primarily through operational energy consumption. Examining various BS configurations and operating conditions suggests that efficiency is not an intrinsic property of technology but rather depends on how BS capacity is provisioned relative to traffic demand. Furthermore, this chapter corroborates existing literature by showing that static power consumption typically dominates the energy consumption of the BSs, which normally operate well below full load and saturation.

Based on the literature review, Figure 7.11 compares the state-of-the-art trends of energy intensity for mobile networks with the intensity ranges derived in this chapter for specific BS configurations. This figure assumes that the examined low and high usage levels (see Table 7.8) correspond to global average usage levels in 2020 and 2030, respectively. Figure 7.11(a) focuses on the widely used per-GB metric and Figure 7.11(b) shows the alternative per-subscription metric (assumed to correspond to the per-UE metric in Figure 7.10). Both figures demonstrate broadly consistent results between this chapter and the literature. However, Figure 7.11(a) shows that the intensity ranges for the specific BS configurations under the high usage level may not reach the projected intensity trend in 2030. Therefore, more efficient BS designs will be necessary to achieve the projections, otherwise projected trends could be considered too optimistic. In contrast, Figure 7.11(b) shows that the intensity ranges obtained in this chapter align with the state-of-the-art trend for both usage levels, and even outperform the projected trend in the *Dense urban*

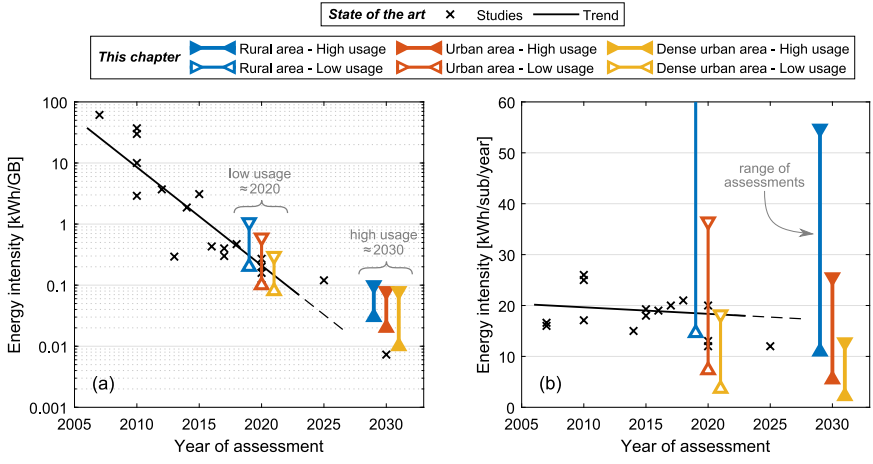


Fig. 7.11 Comparison between this chapter and the state of the art regarding energy intensity metrics for mobile networks (a) per gigabyte of data traffic, and (b) per subscription per year (see Section 3.1.2 for the detailed literature review). Results in this chapter align with state-of-the-art trends, except for the per-GB metric under the 2030 usage level, for which the results are less favorable than the projected trend.

area in 2030. Nevertheless, Figure 7.11(b) highlights that the range of assessments is wider in this chapter than in previous studies, as it depends on the chosen BS configuration and is not averaged at the country or global level.

Although the results of this chapter are consistent with the state of the art, the employed evaluation approach presents several limitations. First, the evaluated BS designs are restricted to predetermined frequency band configurations, representative of deployments observed in Belgium (around 2023). The results are therefore obtained from a limited design space that does not encompass all possible combinations of configuration variables (e.g., carrier frequency, maximum transmit power, and MIMO configuration). In addition, they do not explore potential improvements of the default technological parameters of the integrated RAN model. Second, the examined operating conditions aim to represent typical network deployments and usage patterns in Belgium, but do not capture other possible conditions, particularly those with different network densities. Moreover, the typical daily traffic profile does not account for rare yet extreme peak loads or, in contrast, prolonged periods without traffic demand. Third, the assessment of environmental impacts focuses primarily on operational electricity consumption and briefly analyzes production stage impacts, but excludes distribution and EoL stages. While this focus is relevant for current macrocell BSs in Belgium, it may need to be extended when evaluating, e.g., smaller-scale BSs, shorter lifetimes, or operations with cleaner electricity sources. Fourth, this chapter does not quantify uncertain-

ties, even though they could affect the robustness of certain conclusions, especially those regarding the design trade-offs. Finally, network usage is treated as an exogenous variable, independent of the provided QoS, which prevents the analysis of rebound mechanisms (e.g., increased traffic demand in response to improved QoS) and the associated rebound effects.

Consequently, future research could further strengthen the support for efficient BS designs. A first perspective for future works is optimizing PSSs, particularly their time resolution and activation thresholds, to achieve more stable QoS under varying traffic loads. Alternative PSSs could also be investigated, including power-domain strategies, as well as the exploitation of DTX opportunities for all BS components. Another perspective for future works is to use optimization algorithms to identify Pareto-optimal BS designs that jointly maximize QoS and minimize energy consumption and life-cycle impacts. This may involve optimizing PSSs and frequency band configurations, beyond selecting predetermined settings. For each band, this would include adjusting the transmit power, the bandwidth, the number of layers, the communication protocol, the PA architecture, etc. To better reflect the targets of MNOs regarding user experience, a comprehensive BS evaluation should also include other QoS indicators, such as UL coverage, cell-edge throughput, latency, fairness, etc. Finally, the design principles for more efficient BSs identified in this chapter could be embedded into RAN assessments at the country level to support decision-making by MNOs. Most of these research perspectives could be addressed using the integrated RAN model developed in Part I.

Summary

This chapter illustrates how the integrated RAN model can be applied to evaluate BS designs under typical operating conditions. The examined use cases are representative of RANs in Belgium. The BS designs are based on predetermined 4G-LTE and 5G-NR frequency bands, and the operating conditions are based on a daily traffic profile, three deployment areas, and two UE configurations. However, rebound effects are not considered because the network usage is treated as an exogenous variable with respect to the provided QoS. The results show that BS energy consumption primarily depends on the number of installed frequency bands and the transmit power per band. The environmental impacts of the production stage also scales based on these factors. At low usage, where static power dominates, fixed and dynamic PSSs can substantially reduce power consumption, with additional savings when exploiting DTX opportunities. At high usage, fixed PSSs become ineffective because most BS resources remain active. Dynamic layer sleep can still deliver energy savings, especially for massive-MIMO bands, albeit with potential coverage penalties. In general, dynamic strategies provide more stable QoS over the day and greater energy savings than fixed strategies. The joint QoS-energy analysis shows that combining a low-frequency coverage band with a high-capacity massive-MIMO band results in an efficient BS design. Additional trade-offs emerge with PSSs. The evaluation of energy intensity metrics emphasizes the influence of the normalization perspective. This shows that the conventional per-GB metric is highly sensitive to operating conditions and therefore insufficiently robust to support decision-making. In contrast, the per-MHz metric remains stable across deployment areas and is thus well-suited for first-order energy consumption assessments of RANs at the country level.

8

Prospective evaluation of network deployment strategies in Belgium (2020-2030) from an absolute environmental sustainability perspective

In this second part of the thesis, the integrated RAN model developed in Part I is applied to address specific research gaps identified in Chapter 3. Focusing on the research gaps related to sustainable RAN deployments, this chapter addresses **RQ3** "*What RAN deployment strategy should be adopted by MNOs to transition toward environmental sustainability from an absolute perspective?*" Specifically, it evaluates the absolute environmental sustainability of different RAN deployment strategies in Belgium from 2020 to 2030. This prospective study employs both forecasting and backcasting approaches to construct IPAT-like scenarios that explore possible developments in the number of mobile subscribers, data traffic demand per subscriber, and deployment strategies by MNOs. Following the AESA methodology, the total environmental impacts of these scenarios are first assessed from the bottom up using the integrated RAN model, and then compared with environmental targets derived from the top down. With a focus on climate change, the primary target is the SBTi trajectory established by the ITU, which sets -37% annual GHG emissions for mobile networks between 2020 and 2030 [35]. However, the SBTi approach is debatable in terms of both the allocation of a global carbon budget to

mobile networks and the down-scaling of this budget to Belgium. Therefore, this study also employs different ethical norms and sharing principles to derive alternative carbon budgets for RANs in Belgium over 2020-2030.

The structure of this chapter largely follows the generic backcasting method proposed by Robinson [114]. First, Section 8.1 defines the goal and scope of the prospective study. Then, Section 8.2 constructs different scenarios representing a range of RAN deployment strategies (from business as usual to post-growth) under different network usage trajectories (including forecast, rebound, and sufficiency). Next, Section 8.3 analyzes the resulting trajectories of QoS, energy consumption, and CO₂ emissions at the country level, and discusses the potential for absolute decoupling between energy consumption and network usage in RANs. Adopting an absolute perspective, Section 8.4 subsequently evaluates the environmental sustainability of each scenario and briefly extends the evaluation perspective to social sustainability through the Doughnut Economics framework [59, 60]. Finally, Section 8.5 discusses the main findings of the chapter in light of the state of the art, identifies its limitations, and outlines perspectives for future works. The content of this chapter has not yet been published elsewhere.

8.1 Goal and scope

The goal of this prospective study is to evaluate different future RAN deployment strategies in order to support the transition toward environmental sustainability in mobile Internet access. This study aims to inform and support the strategic planning and decision-making processes regarding RANs by MNOs, network equipment manufacturers, and regulatory bodies, while also guiding research works. To this end, methods and techniques from the field of futures studies are employed to generate and analyze a range of scenarios that capture various RAN deployment strategies and network usage trajectories. Specifically, the study focuses on RANs in Belgium between 2020 and 2030. Adopting a life cycle perspective, the FU of the study is *the provision of mobile Internet access in Belgium from 2020 to 2030 using RANs*. In this definition, the QoS of mobile Internet access is deliberately not quantified, allowing the study to examine diverse RAN usage trajectories and identify potential trade-offs between QoS and environmental impacts. Yet, preserving QoS between 2020 and 2030 is considered desirable, meaning it should not degrade during this period. In the study, QoS is primarily defined in terms of average throughput per UE, but is also extended to traffic congestion and network coverage.

This study focuses on RANs and the scope includes communication-specific components of BSs that support 4G-LTE, 5G-NR and beyond. Conversely, it excludes the mobile core network, the Internet backbone, data centers, and UEs. The integrated RAN model developed in Part I is thus used to assess the QoS and environmental impacts of the deployment strategies. Furthermore, the study focuses on the direct environmental impacts of RANs from a life-cycle perspective. To capture

direct substitution, optimization, and rebound effects within RAN boundaries, environmental impacts are assessed in absolute terms at the country level rather than in relative terms through eco-efficiency metrics. However, the study excludes indirect positive and negative impacts due to effects enabled by mobile Internet access in other economic sectors, such as indirect optimization, substitution, and rebound effects. Associated behavioral and structural effects at the country level are also excluded from the scope [66–69].

Since strategic planning for RAN deployments can only affect subsequent environmental impacts, it cannot alter past impacts retroactively. Accordingly, the prospective study assesses only the impacts of operating RANs from 2020 to 2030, the impacts of producing and distributing new BS components installed after 2020, and the EoL impacts of BS components deinstalled before 2030. Conversely, the study does not attribute to the 2020–2030 period the impacts of component production before 2020 or their EoL treatment after 2030. Thus, the foreground system is modeled using a consequential framework in which the baseline scenario is defined as *the complete shutdown of all RANs in Belgium in 2020 without deinstallation*. Note that other scenarios could also be used as baselines (e.g., leaving RANs operating unchanged). In the integrated RAN model, however, the BS life cycle is modeled using ALCA instead of CLCA, mainly due to its feasibility with existing LCI databases. Thus, the background system is modeled using an attributional framework that reuses IAFs from the BS life-cycle model. As a result, the study relies on a hybrid consequential-attributional framework, which is considered relevant because: (i) the consequential framework is appropriate for informing decision-making in the foreground (e.g., regarding country-level RAN deployments), while (ii) the attributional framework is better suited for modeling the technosphere in the background (e.g., the global IC industry), as it is not significantly transformed by decisions in the foreground [73, 103, 104].

The RAN deployment strategies are then evaluated using the AESA methodology by comparing their bottom-up assessed impacts to top-down assigned SoSOS [74–76]. Although nine planetary boundaries define the SOS [39–42], the prospective study focuses exclusively on climate change. In this context, the study adopts the concept of remaining carbon budget proposed by the IPCC [93]. Since this concept is limited to CO₂ and does not apply to other GHGs, the study only assesses CO₂ emissions from the deployment strategies. Yet, the BS life-cycle model reveals that CO₂ emissions account for around 85% of the total GWP of BSs, with the remainder due to CH₄ emissions from fossil fuels and F-gases from electronics manufacturing [249]. Therefore, focusing on CO₂ captures most of the GWP while aligning with the concept of the remaining carbon budget. Using different ethical norms and sharing principles, illustrative carbon budgets are then assigned to RANs in Belgium over 2020–2030. This approach opens a discussion about the just allocation of the remaining carbon budget and challenges the SBTi trajectory established by the ITU [35].

8.2 Scenario definition

This section defines a set of scenarios combining different RAN deployment strategies and usage trajectories to explore several possible futures. Using the back-casting approach, it aims to reveal potential alternative futures for RANs rather than attempting to accurately predict their likely future. Thus, the prospective study employs two types of scenarios [111–113]: (i) *explorative strategic* scenarios, which explore what might happen in response to strategic decisions by MNOs regarding RAN deployment, and (ii) *normative preserving* scenarios, which examine how RANs can achieve environmental sustainability within the prevailing technosphere. The scenarios are primarily defined based on the analysis of historical RAN deployment and usage trends, as well as forecasts and predictions by ICT sector stakeholders. Scenario generation is also guided by discussions with MNOs and by insights from previous chapters of this thesis.

8.2.1 Main assumptions

The development of scenarios for the prospective study is based on a set of main assumptions regarding to network usage trajectories, deployment areas, and deployment strategies. These assumptions restrict the range of possible scenarios.

- The scenarios are defined with a one-year time step over the ten-year period of the study. Additionally, the RAN deployment and daily usage remain unchanged throughout each year. Therefore, assessing the RAN for one day is sufficient to calculate the annual results.
- The normalized hourly data traffic profile remains unchanged throughout the territory and the study period. Still, the daily data traffic volume per UE may vary from one year to the next.
- The CO₂ emissions from the production and distribution of new BS components are allocated entirely to the year of their installation in the RAN. Similarly, CO₂ emissions from the EoL of BSs are allocated entirely to the year of their deinstallation.
- Typical deployment areas are defined to model the RAN and reflect the varying UE and BS densities across the territory. Each deployment area is considered homogeneous and subject to fixed operating conditions each year.
- In Belgium, three MNOs operate in parallel across the entire territory. In this study, the initial state of RANs in 2020 and the RAN deployment strategies from 2020 to 2030 are assumed to be identical for all three MNOs.
- In Belgium, most outdoor BSs were macrocell BSs in 2020. Therefore, this study only considers macrocell BSs and excludes microcell BSs.

- Throughout the study period, the total number of 4500 BS sites in Belgium is assumed to be fixed, implying that RAN density remains constant. Each BS site can support either three independent BSs for the three MNOs or a single BS shared by all MNOs.
- All BSs are assumed to be powered by the electricity grid. In Belgium, the carbon intensity of the low-voltage electricity grid was 230 gCO₂/kWh in 2019 [246]. Following the historical trend over 2010-2020 [34], the prospective study assumes that this intensity will decrease at a CAGR of -3%/year, reaching 165 gCO₂/kWh in 2030. The carbon intensity factors of all other foreground processes are assumed to remain constant over 2020-2030.

8.2.2 Network usage trajectories

The RAN usage relates to both the total number of UEs and the volume of data traffic per UE. The identification of trajectories for these two factors is based primarily on the analysis of historical trends in Belgium depicted in Figure 8.1.

Figure 8.1(a) shows that the total number of mobile human subscriptions (voice plus data) remained fairly stable from 2014 to 2023, staying slightly above the total population. Among these subscriptions, the share of data subscriptions increased over time and represented most human subscriptions in 2023. However, the growth trend of human data subscriptions is slowing and appears to be stabilizing at the level of the total population. Meanwhile, the number of machine subscriptions increased significantly, representing around 1/3 of total mobile subscriptions in 2023. For the sake of simplicity, this study assumes a constant number of 11.5×10^6 mobile subscriptions throughout 2020-2030, corresponding to Belgium's total population in 2020 [250]. Assuming that the total number of UEs equals the total number of mobile subscriptions, the population density reflects the UE density across the territory. In other words, rather than strictly assessing the QoS per end-user device, the study practically assesses the QoS per inhabitant.

Next, Figure 8.1(b) depicts the evolution of data traffic volume per mobile subscription per day in Belgium. The historical data corresponds to the total data traffic volume (humans plus machines) divided by the number of human mobile data subscriptions only. Since this approach considers total mobile data traffic, it somewhat compensates for the omission of machine subscriptions from the trajectory of mobile subscriptions. Figure 8.1(b) shows that the daily data traffic volume per subscription increased at a CAGR of +40%/year from 2014 to 2023, rising from 11 to 233 MB/sub/day. Based on this trend, the prospective study examines three possible future trajectories of data traffic demand in Belgium.

Linear traffic demand (forecast) According to industry predictions [247, 251, 252], the growth in data traffic volume per mobile subscription is likely to slow down in the future, shifting from exponential to linear growth. The corresponding

8 | Prospective evaluation of network deployment strategies in Belgium (2020-2030) from an absolute environmental sustainability perspective

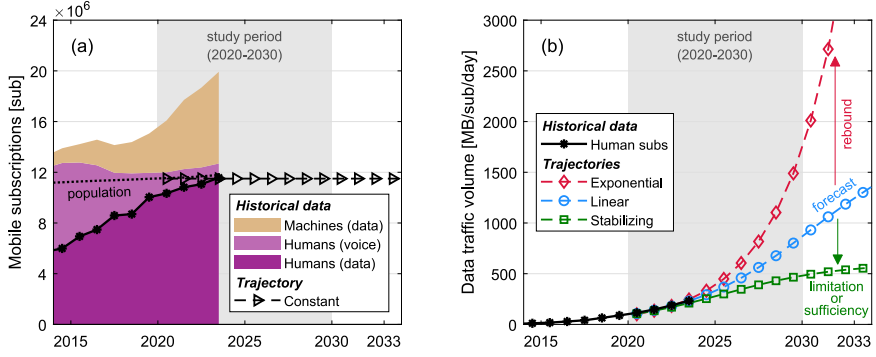


Fig. 8.1 Historical data and trajectories in Belgium for (a) mobile human and machine subscriptions, and (b) daily mobile data traffic volume per human subscription. The prospective study examines one constant trajectory for mobile data subscriptions and three trajectories for data traffic volume per subscription, reflecting the forecast, rebound, and limitation/sufficiency of network usage (data from [248, 250]).

trajectory of daily data traffic volume per UE is modeled as

$$V_{UE}[y] = \begin{cases} \frac{1863}{1 + \exp(-0.28 \cdot (y - 2030))} & \text{if } y < 2030 \\ 931 + 137 \cdot (y - 2030) & \text{if } y \geq 2030 \end{cases}, \quad (8.1)$$

where y denotes the year. This trajectory is considered the base case RAN usage in the prospective study.

Exponential traffic demand (rebound) A second possible trajectory is continuous exponential growth in daily data traffic volume per UE. Assuming a CAGR of +35%/year, this trajectory is modeled as

$$V_{UE}[y] = 100 \cdot 1.35^{y-2020}. \quad (8.2)$$

This trajectory represents a rebound in RAN usage that could eventually lead to a direct rebound effect [48–50].

Stabilizing traffic demand (limitation or sufficiency) A third possible trajectory is a slowdown followed by a stabilization of the daily data traffic volume per UE. Assuming an upper bound of 600 MB/sub/day, this trajectory is modeled by a logistic function as in [JP1] and [253–255], yielding

$$V_{UE}[y] = \frac{600}{1 + \exp(-0.31 \cdot (y - 2025))}. \quad (8.3)$$

This trajectory represents either a forced limitation of mobile Internet usage due to congestion, or a deliberate shift toward sufficiency in usage behavior.

Table 8.1 Deployment areas for radio access network modeling (data from [256–259])

Characteristic		Rural	Urban	Dense urban
Population density [pers/km ²]	typical (range)	50 (0–250)	750 (250–3000)	10 ⁴ (>3000)
Corresponding areas in [JP1] and [131–134]		Wilderness & Rural	Suburban & Urban	Dense urban & Super dense urban
<i>Breakdowns for Belgium</i>				
Population [pers]	total	1.15×10 ⁶	5.75×10 ⁶	4.6×10 ⁶
	(share)	(10%)	(50%)	(40%)
Territory [km ²]	total	22700	7400	600
	(share)	(74%)	(24%)	(2%)
Base station sites [BS]	total	1125	2475	900
	(share)	(25%)	(55%)	(20%)

For scenario assessment, the input variable of the integrated RAN model (i.e., the hourly data traffic volume per UE) is derived from $V_{UE}[y]$ as

$$\bar{v}_{UE}[y, t_h] = \frac{V_{UE}[y]}{24} \cdot \bar{v}_{profile}[t_h], \quad (8.4)$$

where t_h denotes the hour of the day and $\bar{v}_{profile}[t_h]$ is the normalized hourly data traffic profile over one day. This profile is shown in Figure 7.1 and indicates a variation of $\times 7.5$ between the off-peak hour at night and the peak hour at noon.

8.2.3 Deployment areas

Three deployment areas are considered to model RANs across Belgium's territory: **rural**, **urban**, and **dense urban** areas, with typical population densities of 50, 750, and 10⁴ pers/km², respectively. Table 8.1 summarizes the key characteristics of these areas and provides the associated distributions of population, territory, and BS sites in Belgium [256–259]. For instance, 50% of the population lives in the urban area, which covers 24% of the territory and contains 55% of the BS sites. To assess scenarios at the country level, RAN deployments are first assessed separately for each area, and then aggregated similarly to the E³F [131–134] and [JP1].

8.2.4 Initial network deployment

The RAN deployment in Belgium in 2020 is the initial state of the prospective study and is identical in all scenarios. In this state, all BSs use 4G-LTE to provide mobile Internet access. The 1125 BSs in rural areas support a single band at 0.8 GHz, the 2475 BSs in urban areas support a second band at 1.8 GHz, and the 900 BSs in dense urban areas support a third band at 2.6 GHz. Table 7.1 provides detailed

configurations of these frequency bands. The resulting single-, dual-, and triple-band BS configurations are respectively referred to as *1L*, *2L*, and *3L* in Table 8.3.

8.2.5 Deployment strategies

The RAN deployment strategies are defined by *deployment actions*, which include the installation or deinstallation of one or more frequency bands and the upgrade or replacement of BS components. The sequence of these actions is subject to two constraints that restrict the range of possible strategies.

- Only one deployment action is permitted per year and per deployment area.
- A minimum of two years must elapse between deployment actions.

These constraints reflect the practical issues involved in implementing deployment strategies in the real world. Notably, they limit the number of BSs that can be modified each year and assume a minimum latency in strategy realization.

Starting from the initial RAN deployment in 2020, the prospective study examines five possible strategies for future RAN deployment in Belgium until 2030.

Do nothing RANs remain unchanged from their initial state in 2020 and continue operating without modification. Therefore, no deployment actions are planned. This strategy can serve as a basis for comparison with the other strategies.

Business as usual Frequency bands are incrementally deployed in RANs to improve QoS by increasing BS capacity. In 2021, the 4G-LTE band at 1.8 GHz is deployed on rural BSs. Next, the 5G-NR bands at 0.7 and 3.5 GHz are deployed, first in dense urban areas in 2023, and then in urban areas in 2025. Finally, the 5G-NR coverage band at 0.7 GHz is deployed on rural BSs in 2027. This strategy assumes that past deployment patterns continue in the future.

Network sharing Similar to *Business as usual*, except that the three MNOs share all BS components when 5G-NR bands are deployed at a site, including those used for 4G-LTE. Consequently, all BSs are renewed between 2020 and 2030, transitioning from three independent RANs operating in parallel to a single RAN shared by all MNOs. This strategy enables upgrading BSs with up-to-date components but requires deploying BSs with $\times 3$ the bandwidth and transmit power per band. It also requires handling the EoL of deinstalled components. The ITU considers network sharing a key strategy for contributing to climate change mitigation [47].

4G shutdown Similar to *Network sharing*, except that 4G-LTE bands are deinstalled but not replaced when 5G-NR bands are deployed at a site. In rural areas, 5G-NR at 3.5 GHz is deployed alongside the 0.7 GHz coverage band in 2027 to compensate for the deinstallation of 4G-LTE bands, which represent most of the

prior bandwidth. Consequently, 4G-LTE is completely shut down in Belgium after 2027. However, this rapid modernization strategy for RANs is unlikely to be implemented in practice because it would require replacing a large number of UEs that are still operational in order to ensure 5G-NR compliance.

Post-growth A custom communication protocol is proposed for a coverage band at 0.7 GHz and a capacity band at 1.4 GHz, with the aim of reducing energy consumption and CO₂ emissions of RANs while ensuring constant QoS from 2020 to 2030. The capacity and transmit power of the 1.4 GHz band is adapted for each deployment area to provide uniform QoS across the territory. Deployment of the custom BSs starts in rural areas in 2021, where capacity is lowest, followed by dense urban areas in 2023, and urban areas in 2025. The rapid deployment of the custom BSs aims to quickly reduce the total RAN energy consumption. All newly deployed BSs are also shared by the three MNOs. Although unlikely in practice, this transformational strategy aims to identify a potential environmental transition pathway for RANs by combining the design principles for efficient BSs identified in Chapter 7 with a post-growth approach to QoS.

These deployment strategies involve the BS configurations listed in Table 8.3, which relate to the frequency band configurations detailed in Tables 7.1 and 8.2. The operating conditions for these BSs are given in Table 8.4. The study considers six frequency bands: two coverage bands at 0.8 GHz for 4G-LTE and 0.7 GHz for 5G-NR or the custom protocol, and four capacity bands at 1.8 and 2.6 GHz for 4G-LTE, 3.5 GHz for 5G-NR, and 1.4 GHz for the custom protocol. The custom communication protocol in Table 8.2 is based on 5G-NR, except that it assumes a reduced signal PAPR of 5 dB instead of 8 dB to improve the actual PA efficiency (see Section 5.3). This improvement is balanced by a slightly degraded spectral efficiency. In Table 8.3, the first three BS configurations support one to three 4G-LTE bands, the next three BSs support three to five 4G-LTE and 5G-NR bands, and the next one supports two 5G-NR bands only. The last three customized BSs support the custom protocol and are adapted to each deployment area.

Table 8.3 also indicates that certain BS configurations feature PSSs [43–46]. First, the fixed band sleep strategy, *fBS*, activates and deactivates bands on an hourly basis according to a default activation threshold of 10% average resource load. This PSS applies only to the *Ma-L26* and *Ma-N35* bands. Second, the dynamic layer sleep strategy, *dLS*, activates and deactivates spatial data layers for each multi-frame period (every 20 ms) according to a default activation threshold of 30% average load. This PSS applies only to the *Ma-N35* band, which supports ABF. In the custom *2C-R*, *2C-U*, and *2C-DU* configurations, the activation thresholds for both *fBS* and *dLS* were fine-tuned to activate only the necessary resources and provide stable QoS across the BS usage range (see Section 8.3). The third PSS, *dtx*, corresponds to the partial deactivation of PAs during DTX at the symbol time scale. This enables 75% power savings in PAs when they do not transmit a signal over an active sym-

Table 8.2 Custom frequency band configurations

Variable	Ma-C07	Ma-C14		
		Rural	Urban	Dense urban
κ_{prot}	custom	custom	custom	custom
κ_{duplex}	FDD	TDD	TDD	TDD
f [GHz]	0.7	1.4	1.4	1.4
B [MHz]	10	20	20	40
N_L [#]	2	4	8	8
N_{TRX} [#]	2	16	16	16
P_{TX}^{max} [W]	40	5	5	5
P_{TX}^{full} [W]	40	5	5	5
ψ_{hHPBW} [°]	65	90	90	90
G_{TX}^{max} [dBi]	16	20	20	20
κ_{ABF}	without	with	with	with
δ_{cable} [/]	0.8	0	0	0
κ_{RU}	RRU	AAU	AAU	AAU
$\kappa_{PA,arch}$	Doherty	Doherty	Doherty	Doherty
$\kappa_{PA,tech}$	LDMOS	LDMOS	LDMOS	LDMOS

Table 8.3 Complete set of base station configurations

Configuration	1L	2L	3L	3LN	4LN	5LN	2N	2C-R	2C-U	2C-DU
Frequency bands										
Ma-L08	x	x	x	x	x	x				
Ma-L18		x	x	x	x	x				
Ma-L26			x		x	x				
Ma-N07				x	x	x	x			
Ma-N35						x	x			
Ma-C07								x	x	x
Ma-C14 Rural								x		
Ma-C14 Urban									x	
Ma-C14 Dense urban										x
Power saving strategies										
fBS			x		x	x				
dLS					x	x	x	x	x	x
dtx					x	x	x	x	x	x

Table 8.4 Operating conditions of radio access networks

Variable	Rural	Urban	Dense urban
κ_{envi}	rural	suburban	urban
ρ_{BS} [BS/km ²]	0.05	0.33	2
ρ_{UE} [UE/km ²]	50/3	750/3	10 ⁴ /3
$\delta_{UE,A} \delta_{UE,B}$ [/]	0.8 0.2	0.8 0.2	0.8 0.2
V_{UE} [MB/UE/day]	varies following traffic trajectories		

Table 8.5 Summary of the ten scenarios (five strategies × two traffic demand trajectories per strategy) for the prospective study

Strategy	Description	Deployment areas ^a			Scenarios	
		Rural	Urban	Dense urban	Base	Alternative
Initial state	Network state in 2020	<i>1L</i>	<i>2L</i>	<i>3L</i>	–	–
<i>Do nothing</i>	No network modifications compared to 2020	No actions	No actions	No actions	Linear traffic trajectory (forecast)	Stabilizing traffic trajectory (limitation)
<i>Business as usual</i>	Incremental deployment of 4G-LTE and 5G-NR bands to improve throughput, prioritizing the deployment of 5G-NR in urban areas	2021: <i>1L</i> → <i>2L</i> 2027: <i>2L</i> → <i>3LN</i>	2025: <i>2L</i> → <i>4LN</i>	2023: <i>3L</i> → <i>5LN</i>	Linear traffic trajectory (forecast)	Exponential traffic trajectory (rebound)
<i>Network sharing</i>	Similar to <i>Business as usual</i> with network sharing by all three operators	2021: <i>1L</i> → <i>2L</i> 2027: <i>2L</i> → <i>3LN</i> +sharing	2025: <i>2L</i> → <i>4LN</i> +sharing	2023: <i>3L</i> → <i>5LN</i> +sharing	Linear traffic trajectory (forecast)	Exponential traffic trajectory (rebound)
<i>4G shutdown</i>	Similar to <i>Network sharing</i> with shutdown of all 4G-LTE bands, compensated by <i>Ma-N35</i> in rural areas	2021: <i>1L</i> → <i>2L</i> 2027: <i>2L</i> → <i>2N</i> +sharing	2025: <i>2L</i> → <i>2N</i> +sharing	2023: <i>3L</i> → <i>2N</i> +sharing	Linear traffic trajectory (forecast)	Exponential traffic trajectory (rebound)
<i>Post-growth</i>	Prompt deployment of custom sufficiency-oriented base stations with network sharing by all three operators and shutdown of all 4G-LTE bands	2021: <i>1L</i> → <i>2C-R</i> +sharing	2025: <i>2L</i> → <i>2C-U</i> +sharing	2023: <i>3L</i> → <i>2C-DU</i> +sharing	Linear traffic trajectory (forecast)	Stabilizing traffic trajectory (sufficiency)

^a "→" = a deployment action, i.e., installing or deinstalling one or more frequency bands, or upgrading or replacing base station components.

bol. These three PSSs are further discussed in Chapter 7. Furthermore, new BSs deployed after 2020 benefit from the improved technological parameters listed in Table 7.3, whereas BSs already deployed before use default parameter values.

8.2.6 Complete set of scenarios

The complete set of scenarios under study combines the three data traffic demand trajectories with the five RAN deployment strategies. A first subset of five **base** scenarios examines all deployment strategies under the *linear* traffic demand trajectory. These scenarios are used to compare the deployment strategies according to the same forecast usage trajectory. This assumes that the demand for data traffic is an exogenous variable, unaffected by the deployment strategy implemented by MNOs. A second subset of five **alternative** scenarios then assumes that deployment strategies can influence the traffic demand trajectory. Under this assumption, the three scenarios involving deployment strategies based on *Business as usual* are subject to the *exponential* trajectory in order to model a potential rebound effect. The other two strategies are subject to the *stabilizing* trajectory in order to model either a forced usage limitation with the *Do nothing* strategy, or a deliberate sufficiency-oriented usage with the *Post-growth* strategy. Overall, the prospective study examines ten scenarios, summarized in Table 8.5.

8.3 Scenario analysis

This section analyzes the ten scenarios of the prospective study. First, it examines the hourly models of QoS and power consumption for key BS configurations involved in the scenarios, and then applies these models to the one-day data traffic profile in 2029. Next, it studies how the QoS, energy consumption, and CO₂ emissions of RANs may evolve in Belgium from 2020 to 2030. Lastly, the section discusses the potential for absolute decoupling of QoS from energy consumption to achieve an environmental transition in mobile Internet access. Note that this section does not consider the uncertainty in RAN assessments.

8.3.1 Quality of service and power consumption models

The hourly models for all BS configurations involved in the study are obtained using the integrated RAN model developed in Part I. For most BS configurations and all deployment areas, Figures 8.2, 8.3, and 8.4 show models of average DL throughput per UE and average power consumption per BS and per MNO as a function of the hourly data traffic volume per UE. These figures also indicate the daily usage range in 2029 with the *linear* traffic demand trajectory.

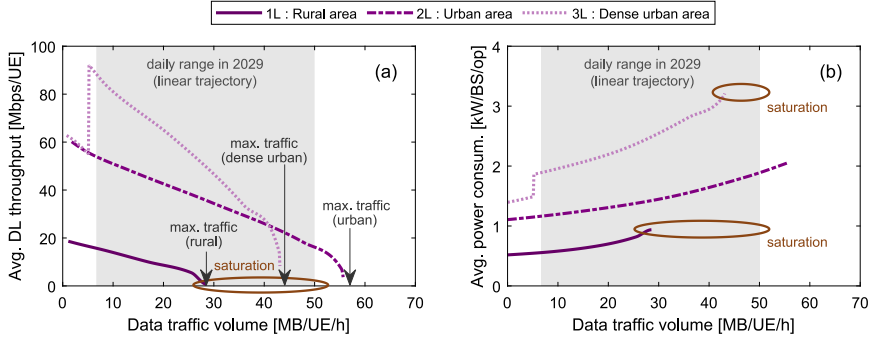


Fig. 8.2 Models for the initial state and the *Do nothing* scenario: (a) average downlink (DL) throughput per user equipment, and (b) average power consumption per base station per operator, as a function of hourly data traffic volume per user equipment.

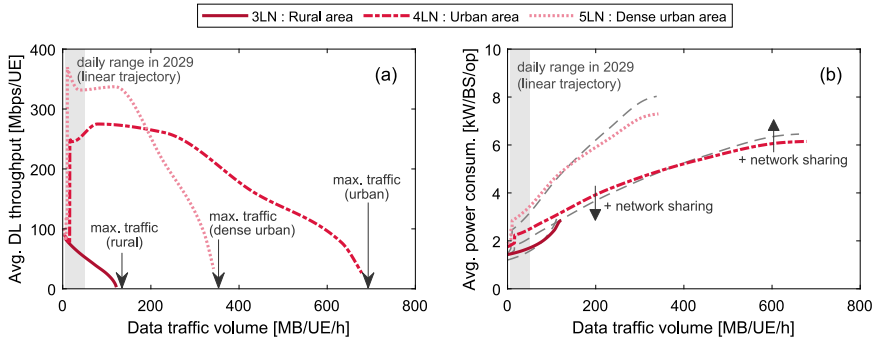


Fig. 8.3 Models for the *Business as usual* and *Network sharing* scenarios: (a) average downlink (DL) throughput per user equipment, and (b) average power consumption per base station per operator, as a function of hourly data traffic volume per user equipment.

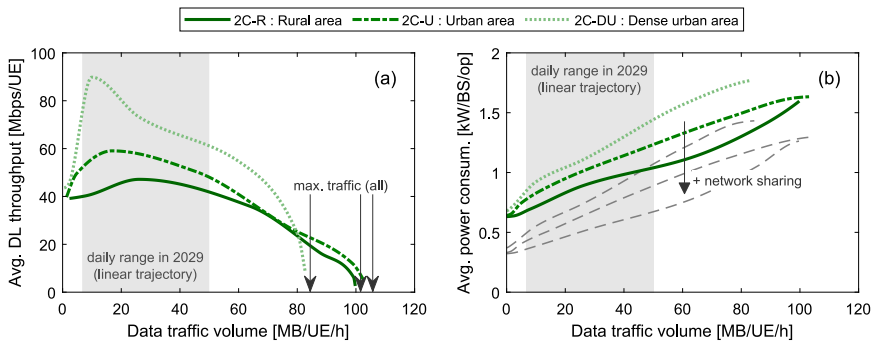


Fig. 8.4 Models for the *Post-growth* scenario: (a) average downlink (DL) throughput per user equipment, and (b) average power consumption per base station per operator, as a function of hourly data traffic volume per user equipment.

Figure 8.2 focuses on the three BS configurations in the initial network state, which remain unchanged in the *Do nothing* scenario. Figure 8.2(a) shows that the average DL throughput per UE is generally the highest for 3L in dense urban area, intermediate for 2L in urban area, and the lowest for 1L in rural area. This reflects the higher physical resource capacity of 3L, i.e., the number of bands, their bandwidth, and their number of spatial data layers. Note that the third band of 3L is activated only above 5 MB/UE/h. However, 3L in dense urban area does not provide the greatest capacity in terms of data traffic volume per UE (around 43 MB/UE/h), as this capacity is higher for 2L in urban area (around 56 MB/UE/h) yet lower for 1L in rural area (around 28 MB/UE/h). Despite its greater resource capacity, the limited traffic capacity of 3L results from the greater number of UEs per BS in dense urban area, as well as closer BSs that increase inter-cell interference at high loads, thus degrading the radio channel quality more rapidly. Next, Figure 8.2(b) shows that a greater number of frequency bands results in higher average power consumption per BS. Looking at the daily RAN usage forecast in 2029 – ranging from 7 to 50 MB/UE/h – the three BS configurations would deliver significantly lower QoS during peak hours than off-peak hours. Specifically, the 1L and 3L configurations would even experience saturation during part of the day.

Figure 8.3 focuses on the three BS configurations involved in the *Business as usual* and *Network sharing* scenarios. Figure 8.3(a) shows that the average DL throughput per UE is lowest for 3LN in rural area and highest for 5LN in dense urban area below 190 MB/UE/h. Above this level, 4LN in urban area provides the highest throughput. This reflects the greater resource capacity of 5LN and 4LN compared to 3LN, particularly due to the *Ma-N35* band. In 4LN and 5LN, capacity band activations occur between 8 and 16 MB/UE/h. Incremental layer activations in *Ma-N35* then roughly stabilize the QoS over a limited traffic range. The greatest data traffic volume capacity per UE is provided by 4LN in urban area (around 680 MB/UE/h), compared to 5LN in dense urban area (around 340 MB/UE/h) and 3LN in rural area (around 120 MB/UE/h). These traffic capacities are much higher than the daily traffic range in 2029, especially that of 4LN in urban area, thereby preventing BS saturation. Next, Figure 8.3(b) shows that a greater number of bands results in higher average power consumption per BS. For these configurations, implementing network sharing can reduce the power consumption per MNO by –20% at low loads thanks to component mutualization. Yet, it increases power consumption by +10% at high loads due to scaled-up components.

Figure 8.4 focuses on the three BS configurations involved in the *Post-growth* scenario. Figure 8.4(a) shows that these configurations are designed to provide similar data traffic volume capacities, which are sufficiently above the data traffic demand forecast in 2029, i.e., 100, 103, and 83 MB/UE/h for 2C-R, 2C-U, and 2C-DU, respectively. Additionally, the average DL throughput per UE is similar in all deployment areas and remains fairly stable across the whole range of daily usage in 2029 thanks to fine-tuned PSSs. Therefore, the custom BS configurations

provide consistent service for different data traffic loads in all deployment areas. Compared to Figure 8.2(a), the custom BS configurations provide a QoS similar to that provided by 2L in urban areas and 3L in dense urban areas at low traffic loads. Yet, they shift the saturation level to $\times 2$ -3 the traffic demand. Next, Figure 8.4(b) shows that the average BS power consumption is quite linear with respect to the data traffic demand and similar for the three custom configurations. Compared to Figure 8.2(b), the power consumption level is similar to that of 2L. For custom configurations, implementing network sharing can reduce the power consumption per MNO from -20% at high loads to -50% at low loads. This demonstrates the relevance of network sharing in the *Post-growth* scenario.

8.3.2 Quality of service throughout the day

To illustrate QoS fluctuations over one day, QoS-related models are applied to the hourly data traffic profile in 2029 under the *linear* trajectory. Figure 8.5(a) shows the resulting hourly average availability of physical resources. Availability < 1 indicates the use of a PSS that deactivates part of BS resources. The 4G-LTE-only (i.e., 1L, 2L, and 3L) and 3LN configuration are fully active during the day due to the absence of PSS and high resource load. In contrast, configurations equipped with *Ma-N35* (i.e., 4LN and 5LN) are never fully active. In between, custom configurations (i.e., 2C-R, 2C-U, and 2C-DU) activate their resources dynamically to follow the traffic profile. Then, Figure 8.5(b) shows the hourly average DL throughput per UE over the day. The 4LN and 5LN configurations have high physical resource capacity and thus operate continuously at low load. They respectively provide around 250 and 350 Mbps/UE during most of the day, except during off-peak hours at night when *Ma-N35* is fully deactivated, causing throughput to drop to around 100 Mbps/UE. In contrast, the 4G-LTE-only configurations provide < 100 Mbps/UE, dropping dramatically during peak hours as they approach saturation. For the custom configurations, throughput remains consistent across deployment areas and fairly stable during the day at around 50 Mbps/UE.

Looking beyond data throughput, Figure 8.5(c) shows the hourly average physical resource load. Throughout the day, 4G-LTE-only configurations experience the heaviest load, followed by custom configurations, and configurations supporting 5G-NR. A maximum QoS threshold is set at a load of 0.7. Above this threshold, QoS is assumed to degrade noticeably due to excessive traffic congestion. Therefore, the prospective study assumes that the network never reaches full saturation in practice. Instead, subscribers force themselves to limit their network usage when the QoS threshold is reached. Additionally, Figure 8.5(d) shows the DL coverage during the day. The minimum QoS threshold for coverage is set at 0.95. Thus, 4G-LTE-only configurations provide poor coverage for most of the day, primarily due to the increased inter-cell interference caused by the high network load. All other configurations remain well above the QoS threshold.

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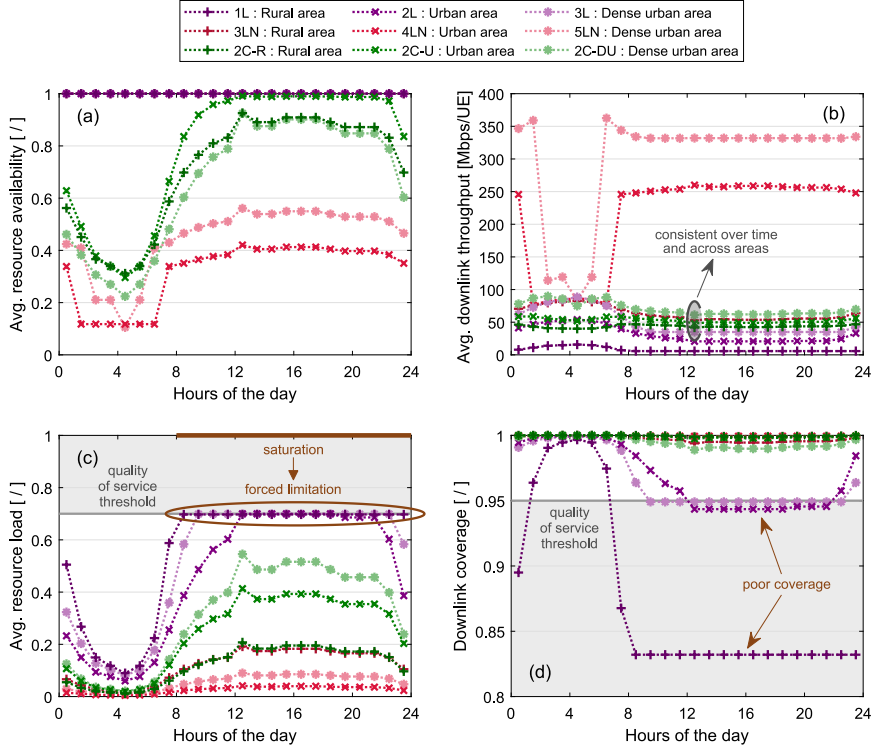


Fig. 8.5 Hourly quality of service profiles over one day in 2029 with the *linear* demand trajectory: (a) average physical resource availability, (b) average downlink throughput per user, (c) average physical resource load, and (d) downlink coverage. 1L, 2L, and 3L are heavily loaded, resulting in low throughput, usage limitation, and poor coverage. 4LN and 5LN are lightly loaded and provide high throughput, except when most resources are deactivated at night. 2C-R, 2C-U, and 2C-DU adapt their available resources to traffic demand and provide consistent throughput over time and across areas.

8.3.3 Quality of service trajectories

The QoS trajectories are obtained by applying the hourly QoS models to each deployment area of the ten scenarios. To summarize the key QoS aspects (i.e., data throughput, traffic congestion, and coverage) into a single performance indicator, QoS is expressed by the comprehensive metric defined by Equation (7.3). The associated load and coverage thresholds are set to $\bar{x}_{QoS} = 0.7$ and $\zeta_{QoS} = 0.95$, respectively. Figure 8.6 depicts the QoS trajectories for the ten scenarios from 2020 to 2030. For each scenario, the figure shows both the daily range (i.e., the range between the lowest and highest hourly values) and the daily average (i.e., the average of hourly values over one day) of the QoS metric per year. The hourly QoS metric for the

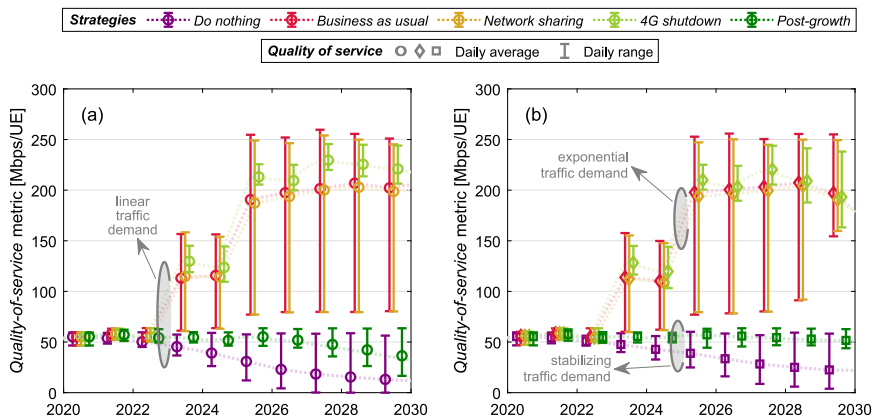


Fig. 8.6 Trajectories from 2020 to 2030 regarding the quality of service (QoS) metric for (a) the base scenarios, and (b) the alternative scenarios. In all scenarios, strategies based on *Business as usual* improve QoS, while the *Do nothing* strategy degrades QoS. With *stabilizing* traffic demand, the QoS of *Post-growth* strategy remains stable over time.

entire RANs is calculated by averaging this metric across the three deployment areas, weighted by the UE share per area. The data traffic volume breakdown per frequency band is also provided for the *base* scenarios in Appendix A.7.

Figure 8.6(a) focuses on the *base* scenarios, which are all subject to the *linear* traffic demand trajectory. The average QoS for the *Business as usual*, *Network sharing*, and *4G shutdown* strategies increases over the years. Through incremental capacity deployment, these strategies improve the QoS from around 50 Mbps/UE in 2020 to > 200 Mbps/UE in 2029. The QoS provided by *Network sharing* is identical to that of *Business as usual* because these two strategies only differ in the physical implementation of BS components, not the deployed resource capacity. With these two strategies, the daily QoS range is wide because certain capacity bands are completely deactivated during off-peak hours (see Figure 8.5). Compared to the previous two strategies, *4G shutdown* offers a slightly higher average QoS with a narrower daily range. Thus, it provides a more stable QoS throughout the day thanks to a more effective adaptation of available resources to traffic demand. Conversely, the QoS of the *Do nothing* strategy degrades over the years due to an increasing network load. Starting in 2027, it even provides zero QoS during the busiest hours of the day when at least one QoS threshold is reached (see Figure 8.5). In between, the average QoS of the *Post-growth* strategy remains stable with a narrow daily range until 2026. After that, it deteriorates as RANs become overloaded.

Next, Figure 8.6(b) focuses on the *alternative* scenarios, i.e., the *exponential* traffic demand trajectory for the *Business as usual*, *Network sharing*, and *4G shutdown* strategies, and the *stabilizing* trajectory for the *Do nothing* and *Post-growth* strate-

gies. Similar to Figure 8.6(a), the QoS for the three strategies based on *Business as usual* improves between 2020 and 2030. However, the average QoS for these strategies begins to decline slightly after 2028, indicating that the data traffic rebound starts to overload the RANs. Conversely, the forced usage limitation with the *Do nothing* strategy results in a QoS that declines less rapidly than with the usage forecast. Thus, the *alternative* scenario is presumably more likely than the *base* scenario with this deployment strategy. In between, the average QoS of the *Post-growth* strategy remains stable with a narrow daily range throughout the study period. This demonstrates that combining the *Post-growth* strategy with the sufficiency-oriented network usage preserves the QoS between 2020 and 2030.

8.3.4 Energy consumption and CO₂ emissions trajectories

As for the QoS, the energy consumption trajectories for the ten scenarios are obtained by applying the hourly power models to each deployment area. Then, the total energy consumption trajectories are calculated by summing the energy consumption per BS multiplied by the total number of BSs per area. Subsequent CO₂ emissions for the use stage are obtained using the carbon intensity factor of the electricity grid mix. The total CO₂ emissions trajectories also include emissions from the production, distribution and EoL stages. Figure 8.7 displays these trajectories for the ten scenarios from 2020 to 2030. Detailed trajectories for the *base* scenarios, including the breakdown of energy consumption per frequency band and of CO₂ emissions per life-cycle stages, are provided in Appendix A.7.

Figure 8.7(a) examines the annual energy consumption. In 2020, this amounts to 130 GWh for all scenarios, which is slightly higher than the 112 GWh estimated in [JP1] using a different modeling approach. In the *base* scenario, the energy consumption under the *Do nothing* strategy increases continuously to reach 182 GWh in 2029. Meanwhile, it doubles to 267 GWh under the *Business as usual* strategy. Following a similar trend, the *Network sharing* strategy reaches 231 GWh in 2029, which represents –14% compared to *Business as usual*. However, these two strategies continually consume more energy than the *Do nothing* strategy because each new band deployed adds to the energy consumption of the previously deployed bands. In contrast, the *4G shutdown* strategy maintains a fairly stable energy consumption over 2020-2030 by deactivating 4G-LTE bands in favor of 5G-NR bands. *Post-growth* is the only strategy that reduces RAN energy consumption over the study period, achieving a –36% reduction to reach 83 GWh in 2029. In *alternative* scenarios, the *exponential* traffic demand increases energy consumption by +16-21% in 2029 for the three strategies based on *Business as usual*, compared to *base* scenarios. Conversely, the *stabilizing* traffic demand reduces energy consumption by –14% and –21% for the *Do nothing* and *Post-growth* strategies, respectively.

Next, Figure 8.7(b) examines the annual CO₂ emissions. In 2020, this amounts to 30 ktCO₂ for all scenarios, which is lower than the 42 ktCO₂ estimated in [JP1]. This difference is mainly due to a different approach to allocating embodied emis-

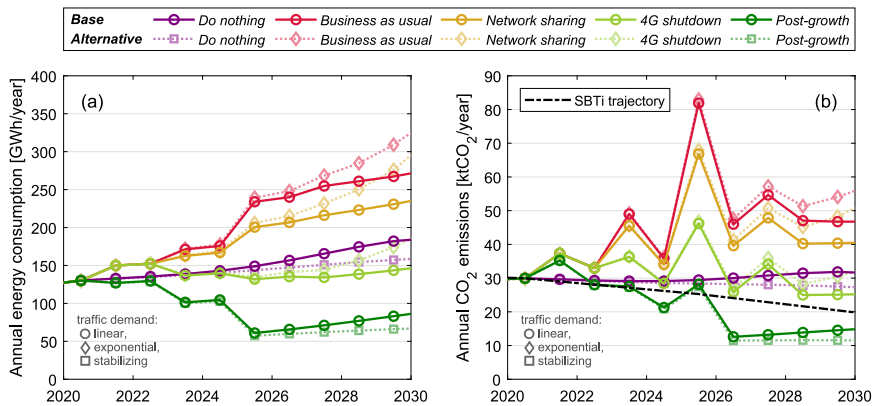


Fig. 8.7 Trajectories from 2020 to 2030 for the base and alternative scenarios regarding (a) the annual energy consumption, and (b) the annual CO₂ emissions. Trajectories for the *Business as usual* and *Network sharing* strategies increase over time, while those for the *Do nothing* and *4G shutdown* strategies remain stable or increase slightly. The *Post-growth* strategy is the only one whose trajectories decrease and align with the SBTi trajectory.

sions. Since the use stage dominates RAN emissions, the main trends observed in energy consumption trajectories are reflected in the CO₂ emissions trajectories. One notable difference is the presence of emission peaks in 2021, 2023, 2025, and 2027, which arise from production, distribution and EoL stages of BS components that are installed or deinstalled in those years. Another difference stems from the decarbonization of the electricity grid, which drives down the trajectories for all scenarios over time. As a result, annual CO₂ emissions increase by +57% for the *base* scenario of the *Business as usual* strategy, reaching 47 ktCO₂ in 2029. Similarly, annual CO₂ emissions decrease by –50% under the *Post-growth* strategy, reaching 15 ktCO₂ in 2029. Of the strategies studied, the *Post-growth* is the only one that aligns with the SBTi trajectory for the two traffic demand scenarios.

8.3.5 Potential for absolute decoupling in radio access networks

Analyzing the relationship between QoS and energy consumption trajectories opens up a discussion about the potential for RANs to absolutely decouple these two aspects. Figure 8.8 illustrates this perspective by plotting the annual RAN energy consumption against the average QoS metric for the ten scenarios of the study. In this figure, the energy consumption is normalized by the total number of UEs in Belgium, ensuring both axes of the graph are expressed per UE. Starting from the same initial state in 2020, the scenarios then follow different trajectories to reach their respective final states in 2029.

8 | Prospective evaluation of network deployment strategies in Belgium (2020-2030) from an absolute environmental sustainability perspective

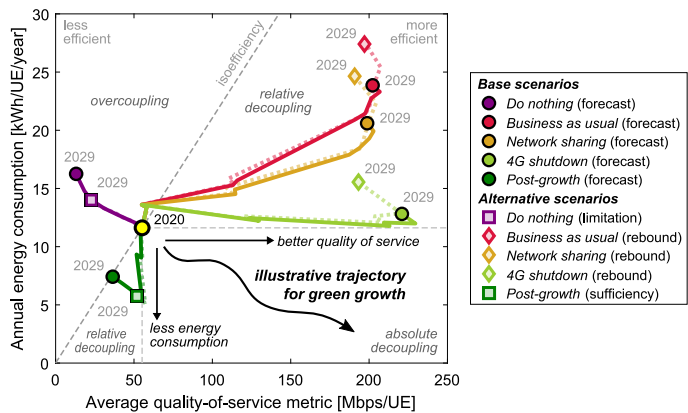


Fig. 8.8 Trajectories of annual energy consumption and average quality of service of radio access networks for the ten scenarios of the study. Starting from the same initial state in 2020, each scenario follows a specific trajectory to reach its final state in 2029. Trajectories are primarily driven by the deployment strategy rather than by traffic demand. The graph identifies three key regions: overcoupling, relative decoupling, and absolute decoupling. Achieving an environmental transition through green growth requires absolute decoupling.

Before examining the scenario trajectories, it is helpful to identify the key regions of the graph. First, an *isoefficiency* curve divides the graph into two parts by passing through the origin and the initial state. All states along this curve offer the same ratio of QoS to energy consumption (i.e., an efficiency factor expressed in Mbps/kWh/year). To the left of the curve, RAN states are less efficient than in 2020, indicating an *overcoupling* of energy consumption to QoS. In contrast, RAN states to the right of the isoefficiency curve are more efficient than the initial state, implying a *decoupling* of energy consumption from QoS. This decoupling can be classified as either relative or absolute [51, 52]. *Relative decoupling* occurs when either the improvement in QoS is faster than the increase in energy consumption, or when the decrease in energy consumption is faster than the decline in QoS. Lastly, *absolute decoupling* occurs when QoS improves simultaneously with a decrease in energy consumption. This region is located at the bottom right of the graph. From a green growth perspective, achieving an environmental transition requires following a trajectory that ensures absolute decoupling [51].

According to this segmentation, the *Do nothing* strategy results in overcoupling between RAN energy consumption and QoS. In contrast, the *Business as usual* and *Network sharing* strategies achieve relative decoupling by improving QoS more rapidly than increasing energy consumption. At the horizontal boundary between relative and absolute decoupling, the *4G shutdown* strategy achieves improved QoS without significantly increasing energy consumption. Still between the two decoupling modes, but at the vertical boundary, the *Post-growth* strategy reduces energy

consumption while maintaining QoS. However, none of the investigated strategies achieves absolute decoupling. Furthermore, Figure 8.8 reveals that the deployment strategy is the main factor that determines the trajectory of a scenario, ahead of the traffic demand. This counterintuitive finding emphasizes the pivotal role of strategic planning decisions by MNOs in shaping the evolution of RANs and the feasibility of an environmental transition.

Another interesting finding when comparing the *base* and *alternative* scenarios for each deployment strategy is that the associated trajectories clearly overlap. Specifically, scenarios with higher data traffic volumes appear to simply extend the trajectory for the lower demand. Additionally, the final states for the three strategies based on *Business as usual* with the traffic demand forecast are located close to the inflection point of the trajectories. Thus, the rebound in traffic demand triggers a recoupling effect with these strategies, resulting in degraded QoS and increased energy consumption. Without the rebound in traffic demand, this recoupling phenomenon would still occur, but with a delay of a few years. Consequently, strategies implemented between 2020 and 2030 should continue beyond 2030 to cope with the growing data traffic demand. For the *Post-growth* strategy, the same recoupling phenomenon appears with the traffic demand forecast compared to the sufficiency scenario. Therefore, combining a *Post-growth* deployment strategy with a sufficiency-oriented traffic demand is essential to preserving QoS while reducing RAN energy consumption and improving energy efficiency.

8.4 Absolute environmental sustainability perspective

Although absolute decoupling may enable an environmental transition, this might not be enough for achieving absolute environmental sustainability. This section therefore evaluates the absolute environmental sustainability of RAN deployment strategies in Belgium using the AESA methodology [74–76]. The first phase of this methodology is the bottom-up environmental impact assessment of the studied activity. Since the study focuses on climate change, this phase involves assessing the cumulative CO₂ emissions of each prospective scenario, which is performed in Section 8.3. Thus, this section focuses on the second and third phases of the methodology: the top-down allocation of the SOS to the studied activity and the result interpretation. For this study, this involves allocating top-down a carbon budget to RANs in Belgium for the period 2020–2030. These assigned carbon budgets are then compared with the CO₂ emissions assessed for each scenario, enabling the evaluation of deployment strategies. To illustrate the normative nature of the top-down allocation process, this section examines four different carbon budgets for RANs. Finally, the section broadens the sustainability evaluation perspective by including a simplified representation of its human dimension.

8 | Prospective evaluation of network deployment strategies in Belgium (2020-2030) from an absolute environmental sustainability perspective

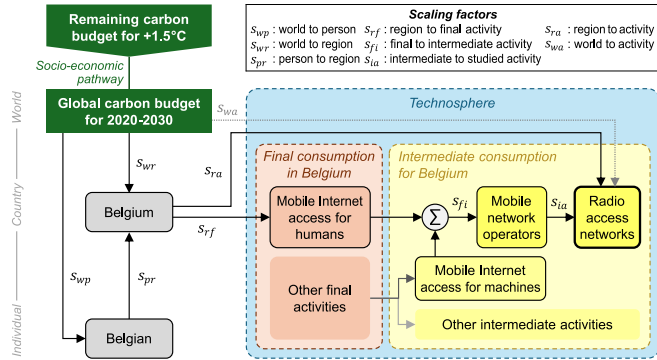


Fig. 8.9 Allocation process of the remaining carbon budget for +1.5°C to radio access networks (RANs) in Belgium from 2020 to 2030. Assigned carbon budget are calculated via scaling factors in three steps: (i) a time-wise allocation over 2020-2030, (ii) a down-scaling to the Belgium population, and (iii) an up-scaling to RANs within the technosphere.

8.4.1 Carbon budget allocation

The process of allocating carbon budgets to RANs in Belgium for the 2020-2030 period is illustrated in Figure 8.9. This process starts with the remaining carbon budget for +1.5°C global warming, in line with the Paris Agreement [33]. The IPCC [93] estimates this budget at 500 GtCO₂ from 2020 onward, with an approximate IQR of 340-735 GtCO₂. The rest of the allocation process consists of three steps. First, the remaining carbon budget is allocated time-wise to the 2020-2030 period based on an appropriate socio-economic pathway. Using the SSP1-1.9, the budget for this period is approximately 310 GtCO₂ [98]. Second, the global budget for 2020-2030 is scaled down to the Belgium population, who are the potential users of RANs. Third, the budget obtained for Belgium is scaled up specifically to RANs, which are part of the technosphere. Both down-scaling and up-scaling involve scaling factors associated with sharing principles based on specific ethical norms [74–76, 109]. All these factors are estimated for the reference year of 2019 and then applied to the entire 2020-2030 period.

8.4.1.1 Down-scaling factors

To illustrate the variety of possible carbon budgets, four down-scaling factors are estimated based on diverging sharing principles [74–76, 109]. These factors determine the amount of CO₂ emissions that the Belgium population has the right to be responsible for across their total consumption between 2020 and 2030 (i.e., their assigned share of the global carbon budget for this period). In Figure 8.9, the direct down-scaling factor from the world to Belgium is denoted by s_{wr} .

Equal per capita A straightforward down-scaling principle is to allocate the same carbon budget per person worldwide, and then proportionally calculate the corresponding budget for the total population in Belgium. This *egalitarian* principle involves two intermediate scaling factors: s_{wp} from the global population to one Belgian, and s_{pr} from one Belgian to the Belgium population. Based on population data (see Appendix A.1), this yields

$$s_{wr} = \frac{s_{pr}}{s_{wp}} = \frac{11.5 \times 10^6 \text{ pers}}{7811.3 \times 10^6 \text{ pers}} = 0.147\%. \quad (8.5)$$

Ability to pay This *prioritarian* principle states that countries with higher-than-average financial capacity must lead efforts to mitigate climate change. Accordingly, these countries are assigned a smaller per-person carbon budget than countries with lower financial capacity. In practice, the equal-per-capita factor is adjusted by the inverse ratio of financial capacity per person in Belgium to the global average. Financial capacity is approximated by the GDP per person adjusted for purchasing power parity and inflation. Based on economic data expressed in constant 2021 international \$ (see Appendix A.1), this yields

$$s_{wr} = 0.147\% \cdot \frac{19425 \$}{60507 \$} \cdot 0.451 = 0.021\%, \quad (8.6)$$

where the factor 0.451 ensures that the sum of the ability-to-pay factors across all countries does not exceed 1.

Economic value To maximize the sum of worldwide welfare, this *utilitarian* principle allocates higher carbon budgets to activities of greater societal utility. Accordingly, countries are assigned carbon budgets proportional to their economic value. A harmonized indicator of this value across countries is the GDP adjusted for purchasing power parity and inflation. Based on economic data expressed in constant 2021 international \$ (see Appendix A.1), this yields

$$s_{wr} = \frac{695 \times 10^9 \$}{151734 \times 10^9 \$} = 0.458\%. \quad (8.7)$$

Grandfathering Another simple and common down-scaling principle is to allocate to a country a share of the global carbon budget identical to its actual share of the global carbon footprint in the reference year. This principle relies on the *acquired rights* to emit CO₂, thereby strengthening the status quo of regional CO₂ emissions distribution. Based on consumption-based CO₂ emissions data for FFI and LULUCF (see Appendix A.1), this yields

$$s_{wr} = \frac{205 \times 10^6 \text{ tCO}_2}{41970 \times 10^6 \text{ tCO}_2} = 0.488\%. \quad (8.8)$$

This slightly higher factor compared to the economic-value factor suggests that the CO₂ intensity per \$ is slightly worse in Belgium than the global average.

8.4.1.2 Up-scaling factors

Alongside the down-scaling factors, two up-scaling factors are estimated using similar sharing principles [74–76, 109]. These factors determine how the Belgium population could allocate their assigned CO₂ emissions for 2020-2030 across their total consumption of products (i.e., goods and services), including mobile Internet access provided by RANs. In Figure 8.9, the direct up-scaling factor from total consumption in Belgium to RANs (i.e., the studied activity) is denoted by s_{ra} .

Economic value This *utilitarian* principle allocates the total carbon budget of a country proportionally to the economic value of activities contributing to its final consumption. Within the technosphere, these activities are divided into final and intermediate activities, as shown in Figure 8.9. Final consumption activities consist of the products that are directly purchased and consumed by households, governments and non-profit institutions serving households. In contrast, intermediate consumption activities relate to the intermediate products in the value chain of final products, either upstream or downstream. Since RANs are intermediate products operated by MNOs, multiple steps are needed to determine their carbon budget from the total carbon budget assigned to Belgium.

1. The economic value of mobile Internet access for human subscribers in Belgium is determined by its share of the FCE. The associated scaling factor, denoted by s_{rf} , is calculated using economic statistics [260, 261] and a household budget survey in Belgium [262].
2. The economic value of mobile Internet access for human subscribers is expanded to include mobile Internet access for machines, whose value is embedded in FCE for various other final activities. The associated scaling factor, denoted by s_{fi} , is estimated by the ratio of total mobile subscriptions to human mobile subscriptions [248]. Therefore, $s_{rf}s_{fi}$ determines the share of Belgium's carbon budget allocated to MNOs.
3. The scaling factor from MNOs to RANs, denoted by s_{ia} , represents the share of economic value that RANs represent in the total value of MNOs. This share is estimated based on MNO revenues and expenditures. Typically, network capital and operating expenditures account for 10% of MNO revenues each [263]. In 2019, it is assumed that 4G-LTE RANs account for the total capital expenditures and 1/3 of the operating expenditures of MNOs.

Overall, this yields

$$s_{ra} = s_{rf}s_{fi}s_{ia} = \frac{1764 \times 10^6 \text{ €}}{359165 \times 10^6 \text{ €}} \cdot \frac{15.1 \times 10^6 \text{ sub}}{12.0 \times 10^6 \text{ sub}} \cdot \left(0.1 + \frac{0.1}{3}\right) = 0.082\%. \quad (8.9)$$

Table 8.6 Carbon budgets assigned to radio access networks in Belgium for 2020-2030

Name	Down-scaling		Up-scaling		Budget [ktCO ₂]
	Principle	Factor [%]	Principle	Factor [%]	
Full utilitarian	Economic value	0.458	Economic value	0.082	1172
Egal-utilitarian	Equal per capita	0.147	Economic value	0.082	377
Prior-utilitarian	Ability to pay	0.021	Economic value	0.082	54
Grandfathering	Grandfathering	0.488	Grandfathering	0.015	222

Grandfathering This simple and common principle allocates the total carbon budget of a country to a product in proportion to its actual carbon footprint in the reference year. This principle relies on the *acquired rights* to emit CO₂, thereby strengthening the status quo of the technosphere structure. Based on consumption-based CO₂ emissions of Belgium (see Appendix A.1) and estimated life-cycle CO₂ emissions of RANs in Belgium (see Section 8.3.4), this yields

$$s_{ra} = \frac{30 \times 10^3 \text{ tCO}_2}{205000 \times 10^3 \text{ tCO}_2} = 0.015\%. \quad (8.10)$$

This significantly lower factor compared to the economic-value factor suggests that RANs are less CO₂ intensive per € than the Belgium economy on average.

8.4.1.3 Assigned carbon budgets

The overall scaling factor for assigning a carbon budget to the studied activity is calculated by combining the down-scaling and up-scaling factors [75, 109] as

$$s_{wa} = s_{wr}s_{ra}. \quad (8.11)$$

Accordingly, four illustrative carbon budgets are assigned to RANs in Belgium for 2020-2030, based on the corresponding global carbon budget (i.e., 310 GtCO₂). These budgets are listed in Table 8.6. The first three illustrative budgets rely on distributive justice theories. The first budget adopts a full utilitarian approach, applying only sharing principles based on economic value. The next two budgets also use utilitarian up-scaling within Belgium, but first perform either egalitarian or prioritarian down-scaling between countries. Adopting a more pragmatic approach that does not directly rely on distributive justice theories, the last budget employs grandfathering for both scaling steps. In this case, the overall scaling factor can also be calculated in one step as $s_{wa} = 30 \text{ ktCO}_2 / 41.97 \text{ GtCO}_2 = 0.000071\%$. The four resulting carbon budgets vary by a $\times 20$ factor from 54 to 1172 ktCO₂. Therefore, the choice of sharing principles greatly influences the assigned carbon budgets, which may affect the subsequent environmental sustainability evaluation.

8.4.2 Evaluation of deployment strategies

To evaluate the environmental sustainability of the RAN deployment strategies, Figure 8.10 compares the cumulative CO₂ emissions of the prospective scenarios with the four illustrative assigned carbon budgets. The figure also shows the breakdown of cumulative CO₂ emissions by life-cycle stage. For each strategy, the difference in cumulative emissions between the *base* and *alternative* scenarios does not exceed $\pm 5\%$. Since this difference is not significant compared to the uncertainty range of scenario assessments, the results for both the *base* and *alternative* scenarios are grouped by deployment strategy in the figure. In contrast, the differences in cumulative emissions across strategies can be considered significant because their IQR generally do not overlap. Therefore, the impact of RANs on climate change is primarily determined by the deployment strategy adopted by the MNOs, prior to their usage by the subscribers.

In Figure 8.10, the cumulative CO₂ emissions of the deployment strategies vary by a $\times 2$ factor, ranging from 220 ktCO₂ for the *Post-growth* strategy to 460 ktCO₂ for the *Business as usual* strategy. The *Do nothing* strategy falls between the two, emitting 300 ktCO₂ from 2020 to 2030. Over the same period, the *Network sharing* and *4G shutdown* strategies reduce the cumulative emissions by -10% and -30% , respectively, compared to *Business as usual*. Moreover, the per-stage breakdown reveals that $> 85\%$ of cumulative CO₂ emissions originate from the use stage (and even 100% in the *Do nothing* scenario), with the remainder mainly attributable to the production stage. These results demonstrate the need for RANs to prioritize reducing their operating electricity consumption and decarbonizing the source of this electricity to mitigate their impact on climate change.

Following the AESA methodology, the cumulative CO₂ emissions of the deployment strategies must then be compared to their assigned carbon budgets. Thus, Figure 8.10 also depicts these budgets and their IQRs (which are proportional to the IQR of the remaining carbon budget). All strategies significantly exceed the prior-utilitarian budget, by a $\times 4-9$ factor. Conversely, they all remain well below the full utilitarian budget, by a $\times 3-6$ factor. Accounting for IQRs, the three strategies based on *Business as usual* align with the egal-utilitarian carbon budget, while the *Do nothing* and *Post-growth* strategies fall distinctly below this budget. Similarly, the *Do nothing* and *Post-growth* strategies respect the grandfathering budget, while the other three substantially exceed it. Judging the environmental sustainability of deployment strategies therefore depends on the ethical norms adopted for down- and up-scaling. Given the relatively low CO₂ intensity of RANs compared to their economic value, the deployment strategies are less constrained when the budget allocation relies mainly on utilitarian norms. However, the societal utility of RANs and mobile Internet access could be debated and measured using indicators other than economic value.

In practice, implementing a transition to environmental sustainability requires selecting a single carbon budget and then developing a consistent deployment

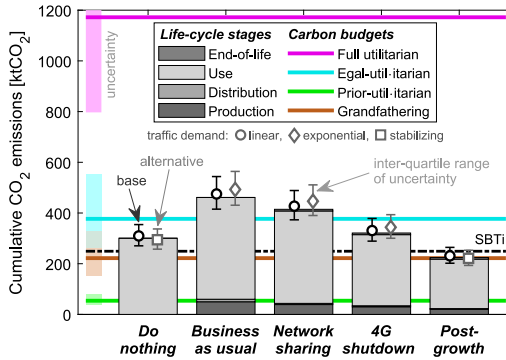


Fig. 8.10 Evaluation of the absolute environmental sustainability of radio access network deployment strategies by comparing their cumulative CO₂ emissions over 2020-2030 with their illustrative assigned carbon budgets. Base and alternative scenarios are grouped by strategy, and emissions are broken down by life-cycle stage. Strategies are less constrained in terms of CO₂ emissions when the carbon budget is assigned using utilitarian norms.

strategy. In this context, the SBTi can serve as a reference because it aims to allocate the global CO₂ emission trajectory for +1.5°C among all economic sectors [35]. Thus, Figure 8.10 also depicts the cumulative CO₂ emissions associated with the SBTi trajectory for RANs in Belgium. The resulting carbon budget is slightly greater than the grandfathering carbon budget, which is not surprising since the SBTi approach is primarily based on the grandfathering norm [77]. This choice seems reasonable because the SBTi budget falls roughly in the median position of the four illustrative carbon budgets. However, the question may arise as to whether grandfathering is a just approach to allocating carbon budgets. Yet, recommendations on the most just approach to allocation are beyond the scope of this thesis and should involve other research disciplines and stakeholders (e.g., industrial and political actors, as well as users) to ensure a relevant and participatory outcome.

8.4.3 Radio access networks within the Doughnut

Alongside the environmental perspective, the concept of sustainability also includes a social dimension [57]. Since the AESA focuses on environmental sustainability, this section investigates an approach to broaden the evaluation perspective of RAN deployment strategies to account for both the environmental and social dimensions of sustainability. This extension is based on the Doughnut Economics framework [59, 60], which defines a "safe and just space for humanity" (shaped like a doughnut) between an outer boundary, the "ecological ceiling", and an inner boundary, the "social foundation". In the prospective study, the ecological ceiling is examined solely with respect to climate change, and the social foundation solely with respect to networks, specifically Internet access. Accordingly, Figure 8.11 plots

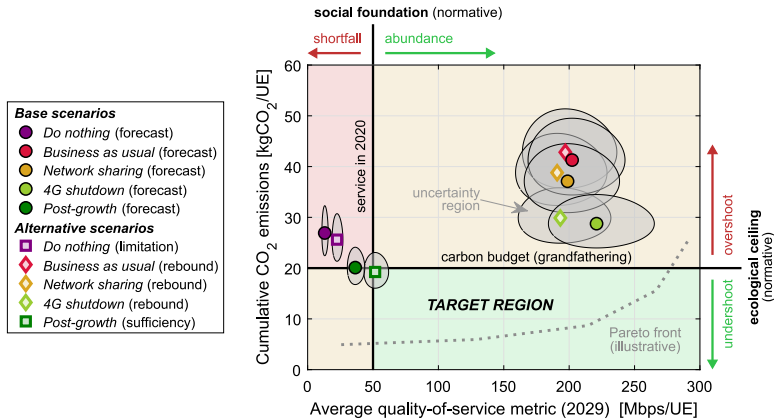


Fig. 8.11 Evaluation of the environmental and social sustainability of radio access network deployment strategies in terms of cumulative CO₂ emissions over 2020-2030 and average quality of service in 2029. Inspired by the Doughnut Economics framework, the grandfathering carbon budget is set as the ecological ceiling and the service in 2020 as the social foundation. Only the sufficiency scenario of the *Post-growth* strategy falls within the target region. Other scenarios could be identified in this region up to the Pareto front.

the ten scenarios of the study based on their cumulative CO₂ emissions over 2020-2030 along the y-axis and their average QoS metric in 2029 along the x-axis. As in Section 8.3.5, the cumulative emissions are normalized by the total number of UEs in Belgium, ensuring that both axes are expressed per UE.

This representation first enables the identification of trade-offs between the cumulative CO₂ emissions of deployment strategies and their average QoS in 2029. From a bi-objective optimization perspective intended to jointly minimize CO₂ emissions and maximize QoS, Figure 8.11 also distinguishes between dominant and dominated strategies. For instance, the *4G shutdown* and *Post-growth* strategies dominate the *Do nothing*, *Business as usual*, and *Network sharing* strategies. The best scenarios for the two dominant strategies occur with the lowest traffic demand, namely the forecast scenario for the *4G shutdown* strategy and the sufficiency scenario for the *Post-growth* strategy. Additionally, the uncertainty regions (calculated based on their IQRs) show that certain strategies are distinct from others (e.g., *Do nothing*), while others overlap (e.g., *Business as usual* and *Network sharing*).

Normative thresholds can then be specified to represent the ecological ceiling and social foundation. Figure 8.10 illustrates this approach by setting the grandfathering carbon budget as the ecological ceiling along the y-axis (around 20 kgCO₂/UE) and the QoS of 2020 as the social foundation along the x-axis (around 50 Mbps/UE). This results in a graph with four quadrants. A strategy in the upper left quadrant overshoots the ecological ceiling and falls short of the social foundation, which is the worst case. A strategy in the upper right (resp.

lower left) quadrant overshoots (resp. undershoots) the ecological ceiling and provides an abundance (resp. shortfall) of the social foundation. Thus, these two quadrants satisfy only one dimension of sustainability. To be considered environmentally and socially sustainable, a strategy must therefore lie in the lower right quadrant and satisfy both boundaries of the Doughnut Economics. Of all the scenarios, only the sufficiency scenario of the *Post-growth* strategy falls within this target region. Yet, its margin from the thresholds is very narrow and its uncertainty region even extends beyond them. Therefore, none of the examined scenarios demonstrates robustness in reaching the target region.

8.5 Discussion

Environmental sustainability in mobile Internet access cannot be addressed solely through relative efficiency improvements. Instead, it requires reducing absolute environmental impacts over time to align with sustainability targets such as the SBTi trajectory defined by the ITU. The literature review in Chapter 3 identifies four prospective studies that evaluate RANs at the country level. These studies generally explore both supply- and demand-side scenarios, providing valuable insights into the main drivers of total energy consumption and GHG emissions. However, none of them evaluates whether the explored scenarios align with absolute environmental sustainability targets. To address this gap, this chapter uses Belgium as a case study and applies the integrated RAN model developed in Part I to evaluate prospective RAN deployment strategies from 2020 to 2030. Prospective scenarios are developed using both explorative and normative approaches, including back-casting, in order to reveal potential futures compatible with sustainability targets. Adopting an absolute sustainability perspective, scenario evaluation follows the AESA methodology by combining bottom-up impact assessments with top-down allocation of carbon budgets. This approach therefore supports decision-making by MNOs beyond the sole analysis of relative efficiency metrics or the decoupling between QoS and energy consumption.

Based on the literature review, Figure 8.12 compares the impact trajectories obtained in this chapter with those reported in the four state-of-the-art prospective studies. Figure 8.12(a) focuses on annual energy consumption and Figure 8.12(b) presents the corresponding annual CO₂ emissions. To enable comparison across studies, all trajectories are indexed to 1 in 2020. For each strategy explored in this chapter, the figure depicts only the base scenario under the traffic demand forecast, as the alternative scenarios do not differ significantly. The trajectory comparison demonstrates that *Business as usual* and *Network sharing* are consistent with the baseline scenarios reported in the literature for both energy consumption and CO₂ emissions. The other end of the range of state-of-the-art scenarios corresponds to *Do nothing* and *4G shutdown*. Beyond this range, the *Post-growth* strategy significantly outperforms reductions in energy consumption and CO₂ emissions reported

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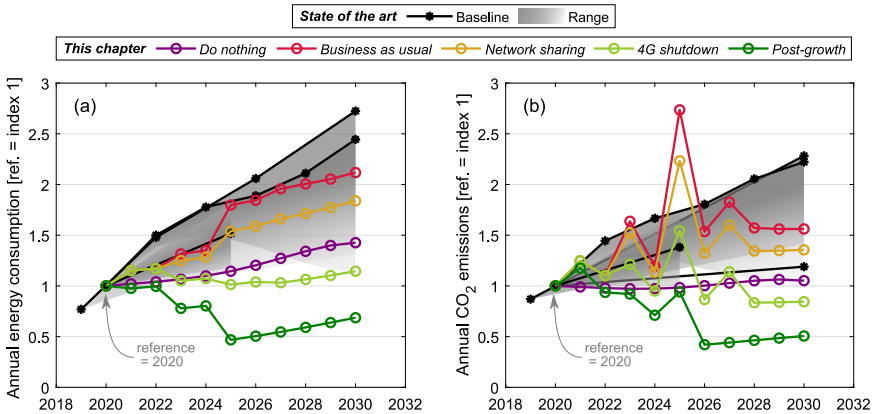


Fig. 8.12 Comparison between this chapter and the state of the art regarding prospective scenarios from 2020 to 2030 for radio access networks at the country level in terms of (a) annual energy consumption, and (b) annual CO₂ emissions (see Section 3.1.3 for the detailed literature review). Most of the strategies examined in this chapter (only base scenarios are depicted) align with the range of state-of-the-art scenarios, except for the *Post-growth* strategy, which achieves significantly greater impact reductions.

in previous studies. This outcome stems from the combination of efficiency and sufficiency measures on the supply side, which enables alignment with the SBTi trajectory. In addition to impact trajectories, this chapter also provides detailed assessments of QoS trajectories for each scenario, which is a key contribution compared to the four state-of-the-art studies.

Although this chapter provides valuable insights into the role of MNOs and mobile users in shaping future RAN trajectories, several limitations arise from the adopted modeling approach. First, RANs are represented by three homogeneous deployment areas at the country level, which does not represent the actual network heterogeneity and cannot capture site-specific characteristics. While this modeling strategy is suitable for informing strategic planning, it is not intended for detailed network planning. Moreover, identical RAN deployment strategies are assumed for the three MNOs in Belgium. Second, the explored deployment strategies are deliberately constrained by simplifying assumptions, including a fixed number of sites (thereby excluding network densification), limited deployment actions (with a minimum delay between them), and a focus on macrocell BSs (thereby excluding microcells). Regarding the network usage, a set of illustrative traffic demand trajectories is used for a fixed normalized daily traffic profile, the number of subscriptions is assumed to remain constant over 2020-2030, and the machine subscriptions are omitted. Overall, these assumptions affect the realism of explored scenarios. Third, the examined demand trajectories are practically treated as exogenous inputs to the integrated RAN model without modeling an endogenous

coupling between QoS and traffic demand. As a result, rebound mechanisms are only addressed by analyzing alternative trajectories rather than modeling an internal feedback loop, thereby limiting the assessment of rebound effects. Finally, this chapter explores a limited set of prospective scenarios that are neither predictive nor exhaustive. Since the associated deployment strategies are not derived from formal optimization, they cannot be considered optimal. Thus, other combinations of deployment actions could potentially yield better strategies.

Additional limitations of this chapter relate to the assessment of environmental impacts and the evaluation of absolute environmental sustainability. First, the impact assessment focuses on climate change and considers CO₂ emissions only, which does not cover the nine planetary boundaries defining the SOS. As a result, potential burden shifting between impact categories are not captured. Second, the system boundary is restricted to the life-cycle stages of BS components and excludes UEs, the core network, and data centers, as well as indirect impacts enabled in other sectors. Thus, deployment strategies that appear favorable within RAN boundaries (e.g., *4G shutdown*) could lead to different conclusions under an extended system boundary. Third, apart from electricity grid decarbonization, the background system is assumed to remain unchanged over the study period, thereby excluding evolutions in the technosphere and associated changes in IAFs. Finally, applying the AESA methodology introduces additional challenges. Specifically, conclusions about whether a scenario achieves absolute sustainability depend strongly on the ethical choices underlying the normative down-scaling and up-scaling principles, as well as on the availability and quality of data used to estimate the scaling factors. More broadly, applications of future-oriented AESA remain largely underdeveloped in the literature, resulting in unresolved methodological tensions within the chapter. These tensions are particularly evident in the pragmatic choice of an hybrid consequential-attributational framework and in the allocation of the global remaining carbon budget over time.

Consequently, future research could further strengthen both the realism and the decision-making relevance of prospective RAN evaluations. First, future works could broaden the range of explored scenarios to more accurately reflect actual deployment strategies. They could also directly incorporate rebound mechanisms into the RAN model and assess additional QoS indicators related to user experience. Other perspectives for future works is to extend the environmental impact assessment beyond climate change and to broaden the system boundaries, including at least the impacts of UEs, and, when relevant, discussing indirect effects in other sectors. Another key perspective for future research is to use optimization algorithms to systematically explore the possible deployment strategies and traffic demand trajectories instead of relying on a limited set of scenarios. For instance, this could involve assessing whether absolute decoupling between QoS and environmental impacts is achievable in RANs and under which conditions. The operationalization of the Doughnut Economics framework could also be supported

by a bi-objective optimization that jointly minimizes cumulative GHG emissions and maximizes the QoS. Specifically, this could help identify robust Pareto-optimal scenarios with respect to the normative thresholds of the "safe and just space for humanity" (i.e., the ecological ceiling and social foundation). In this context, future research could further develop participatory and interdisciplinary approaches to refine the definition of a social foundation for mobile Internet access and improve methods for allocating the remaining carbon budget over time.

Summary

This chapter illustrates how the integrated RAN model can be applied within a LCE framework to inform strategic planning of RAN deployment. Combining five deployment strategies with three traffic demand trajectories, ten prospective scenarios are developed for RANs in Belgium from 2020 to 2030. Scenario analysis shows that trajectories of QoS, energy consumption and CO₂ emissions are primarily driven by the deployment strategy rather than by traffic demand. *Do nothing* gradually degrades QoS and leads to forced usage limitation due to network congestion. *Business as usual* improves QoS through incremental capacity deployment but increases energy consumption and CO₂ emissions. In comparison, *Network sharing* partially reduces the total impacts. By transitioning to 5G-NR only, *4G shutdown* stabilizes energy consumption while improving QoS. In contrast, the *Post-growth* strategy preserves QoS with the stabilizing traffic demand and reduces energy consumption and CO₂ emissions by combining network sharing, custom frequency band configurations, and fine-tuned PSSs. This strategy is the only one aligning with the SBTi trajectory set by the ITU. However, none of the examined strategies achieves absolute decoupling between QoS and energy consumption. Following the AESA methodology, alternative carbon budgets are then assigned to RANs in Belgium for 2020-2030 and compared to the cumulative CO₂ emissions of each scenario. Outcomes of this absolute environmental sustainability evaluation strongly depend on the normative basis for carbon budget allocation. A simplified environmental-social sustainability evaluation shows that the *Post-growth* strategy with stabilizing traffic demand is the only "safe and just" scenario examined.

9

Conclusion

Digitalization increasingly affects human activities through ICTs and is often presented as a means to improve quality of life while mitigating environmental impacts. Among ICT services, this thesis focuses on *mobile Internet access* provided by cellular RANs in 4G-LTE and 5G-NR. In the context of climate change, mobile networks must undergo an environmental transition to reverse their historical upward trend of GHG emissions. In line with the Paris Agreement, the ITU has set a GHG reduction target of -37% for mobile networks between 2020 and 2030. One conventional strategy to meet this target is to improve network energy efficiency, assuming that absolute decoupling between GHG emissions and mobile data traffic is possible. However, efficiency improvements alone may be insufficient for a successful transition because rebound effects can offset the expected energy savings. Therefore, sufficiency strategies may also be necessary. At the same time, deteriorating the QoS of mobile Internet access would be undesirable, as this service has become essential for fulfilling human needs in modern societies.

Adopting a strong sustainability perspective, the goal of this thesis was

to support the implementation of QoS-informed transition strategies for RANs toward environmental sustainability in mobile Internet access.

Specifically, the thesis aimed to enable researchers, MNOs, and manufacturers to assess the techno-environmental performances of different RAN configurations, support the eco-design and optimization of next-generation BSs, and inform decision-making and strategic planning for sustainable RAN deployment strategies. More broadly, this thesis sought to illustrate how environmental sustainability can be systematically incorporated into engineering research.

9.1 Contributions and key findings

The thesis began with a review of frameworks and methods for operationalizing environmental sustainability in engineering practices in Chapter 2, followed by a review of state-of-the-art RAN models and assessments in Chapter 3. These two chapters situated and motivated the specific contributions of the thesis in relation to existing literature and scientific knowledge. The rest of the thesis followed a structured LCE approach and was organized into two parts. Part I developed an integrated parametric model of RANs across Chapters 4, 5, and 6. This model was subsequently leveraged in Part II through two applications specific to Belgium in Chapters 7 and 8. These applications illustrated how the proposed model can be used to inform decision-making and strategic planning. The main contributions and key findings of these chapters are summarized below in response to the three research questions formulated in the introduction.

RQ1 *How can a RAN be modeled to simultaneously assess its QoS and direct environmental impacts under given operating conditions?*

Existing RAN models primarily focus on QoS and power consumption but generally overlook environmental impacts from a life-cycle perspective. Moreover, these dimensions are typically modeled separately rather than within a unified framework. Therefore, this thesis developed an integrated RAN model that simultaneously assesses QoS, energy consumption, and life-cycle environmental impacts. This RAN model combines three separate BS models for (i) communication performance, (ii) power consumption, and (iii) life-cycle environmental impacts. These three models focus on large-cell commercial BSs supporting sub-6 GHz frequency bands in 4G-LTE and 5G-NR. Using a modular and parametric modeling approach, they were constructed from the bottom up based on multiple configuration variables representing BS features and operating conditions. To ensure applicability in real-world contexts, the technological model parameters were calibrated using regression analysis of specific empirical data, including on-site measurements, technical documentation, and BS component teardowns. At the network level, the BS models are controlled by a traffic model through physical resource load. To represent the useful RAN service, the traffic model is driven by the hourly data traffic volume per UE. Overall, the integrated RAN model enables flexible and consistent assessments of a wide range of configurations under given operating conditions. The associated quantified uncertainty ranges allow for more robust result interpretation by enabling systematic uncertainty analysis.

Since the BS communication performance model relies on existing models, it does not constitute a novel contribution of the thesis. The main contributions instead lie in the development of the BS power consumption and life-cycle environmental impact models. The proposed power model represents the BS as a set of functional components, including the DBB, AFE, AS, ACS, and UPS,

complemented by a detailed power model of PAs. Each component is modeled for multiple operating modes and usage levels across different time scales, enabling the analysis of both fixed and dynamic PSSs. Using physical resource load rather than data traffic volume to represent the BS usage level ensures robust and site-independent BS models. Following the LCA methodology, the proposed BS life-cycle model encompasses multiple impact categories and covers all life-cycle stages, from production to distribution, use, and EoL. While the use stage is directly modeled using the BS power consumption model, the production stage is modeled by aggregating the impacts of producing physical BS components, including the BBU, RUs, AUs, PSU, and external cables. Specific environmental impact factors for these components were calculated using the ecoinvent database. In general, these models demonstrated good precision and accuracy through uncertainty quantification and validation, emphasizing the value of using specific empirical data for model development and calibration.

Applying both models to typical BS configurations provided insight into BS eco-design. The results showed that static power consumption accounts for a substantial share of total BS energy consumption. In traditional macrocell BSs, PAs dominate the full-load power, whereas massive-MIMO significantly increases the contribution of TRXs. The detailed PA power model also revealed that the PAPR of 4G-LTE and 5G-NR waveforms degrades the efficiency of conventional PA architectures. In microcell BSs, both static and total power consumption are dominated by the DBB. Implementing sleep modes can significantly reduce the power consumption at no load. From a life-cycle perspective, the use stage dominates BS environmental impacts across all categories. The production stage also contributes significantly to certain impact categories, especially mineral and metal resource use. In contrast, the distribution and EoL stages have negligible impacts. These findings indicate that reducing BS energy consumption and opting for low-impact electricity sources are the key mitigation levers. Conversely, increasing the use of recycled materials to produce BS components and recycling the components at EoL only marginally reduce the total BS life-cycle impacts.

RQ2 *What BS designs are efficient in terms of QoS and direct environmental impacts under typical operating conditions?*

Efficient BS designs require balancing installed capacity, which affects the provided QoS, against total energy consumption, which accounts for most direct environmental impacts. This thesis analyzed these trade-offs by evaluating realistic BS designs based on predetermined frequency band configurations. The results showed that BS energy consumption scales primarily with the number of installed frequency bands and the transmit power per band. The environmental impacts of the production stage scale similarly. PSSs can substantially improve BS efficiency but inherently entail QoS-energy trade-offs. At low usage, where static power dominates, both fixed and dynamic PSSs can substantially reduce power consumption,

with additional savings when exploiting DTX opportunities. At high usage, however, fixed PSSs become less effective because most resources remain active. Dynamic layer sleep can still deliver residual energy savings, especially for massive-MIMO bands. Yet, deactivating spatial layers reduces the beamforming gain, which can degrade coverage. Overall, the results showed that dynamic PSSs generally provide more stable QoS over the day and greater energy savings than fixed PSSs, making them preferable when their added complexity is manageable.

Evaluations of BSs under typical operating conditions for RANs in Belgium revealed that an efficient macrocell design combines a traditional low-frequency band with a high-capacity band featuring massive-MIMO. This combination preserves BS coverage through the lower frequency band while enabling high data throughput through the higher frequency band. Restricting the design to two bands minimizes the systematic energy penalty associated with the static power consumption of each additional band. Moreover, massive-MIMO offers opportunities for PSSs to dynamically adapt the number of active spatial layers to the number of active UEs and their data traffic demand. Further results for microcell BSs showed that their deployment is not always beneficial. Although they have low individual energy consumption, they require a high site density for coverage, which may offset their energy savings compared to macrocell BSs. Therefore, deploying microcell BSs is mainly relevant in dense urban areas.

RQ3 *What RAN deployment strategy should be adopted by MNOs to transition toward environmental sustainability from an absolute perspective?*

In general, environmental transitions require action on both the supply and demand sides. For RANs, the supply side mainly involves MNOs, whose deployment strategies determine network configuration, while the demand side concerns mobile users, whose data traffic demand shapes network usage. Transition strategies on both sides may combine efficiency and sufficiency measures, reducing the direct environmental impacts of RANs while avoiding rebound effects. A key element in planning a transition toward environmental sustainability is defining appropriate targets for RANs. From an absolute perspective, the AESA methodology provides an approach to allocate global environmental targets, such as planetary boundaries, to specific products. In particular, this approach enables carbon budgets to be assigned to RANs beyond the SBTi trajectory set by the ITU. However, the resulting targets strongly depend on the normative basis underlying the allocation process, which may reflect different distributive justice theories. Extending the sustainability evaluation to include the social foundation of the Doughnut Economics framework requires strategies that also ensure an acceptable QoS.

Focusing on climate change, this thesis evaluated RAN deployment strategies in Belgium using prospective scenarios from 2020 to 2030. Scenario analysis showed that the QoS, energy consumption, and CO₂ emissions of RANs are primarily driven by the deployment strategy rather than by traffic demand. This

finding therefore indicates that MNOs play a predominant role in shaping future RAN trajectories compared to mobile users. Among the strategies investigated in this thesis, the post-growth strategy is the only one that simultaneously preserves QoS and decreases both energy consumption and CO₂ emissions, aligning with the SBTi trajectory. This strategy relies on network sharing by MNOs, early shutdown of 4G-LTE bands in favor of customized frequency bands, deployment of BS configurations tailored to their operating conditions, and fine-tuned PSSs that dynamically adapt active resources to provide stable QoS. In contrast, the business-as-usual strategy improves QoS but also increases energy consumption, network sharing alone offers limited mitigation effects, and shutdown of 4G-LTE in favor of deployments with 5G-NR only improves QoS but merely stabilizes energy consumption. The least favorable strategy is to do nothing, as it leads to network congestion that forces usage limitations while still increasing energy consumption. Furthermore, none of the examined strategies achieves absolute decoupling between QoS and energy consumption.

Overall, these findings support a paradigm shift from capacity-driven RAN deployment strategies toward sufficiency-oriented strategies. Such strategies should involve: (i) sharing network infrastructure where feasible, (ii) deploying capacity selectively on BSs to match their actual operating conditions, (iii) limiting the number of simultaneously active frequency bands, and (iv) supporting measures that limit traffic growth and consequently avoid rebound effects. While these strategies continue to rely on efficient technologies and BS designs, they no longer treat relative efficiency metrics as the sole performance targets.

9.2 Recommendations

Environmental sustainability in mobile Internet access cannot be achieved by a single actor or through isolated technical optimizations. Instead, it is a systemic challenge arising from the interactions between network technologies, deployment strategies, standardization, regulations, and usage behavior. The key findings of this thesis can thus be translated into practical recommendations for key stakeholders, including network equipment manufacturers, MNOs, and mobile network users, as well as for governance and decision-making processes.

9.2.1 For network equipment manufacturers

Network equipment manufacturers should prioritize reducing the static power consumption of BS components. Design efforts should focus on minimizing idle power in PAs and TRXs, as well as on implementing deeper sleep modes across all hardware components. BS architectures should also be designed to support advanced PSSs, including dynamic activation of frequency bands and spatial data layers, and enabling fast transitions between operating modes. In addition, DTX op-

portunities should be systematically exploited, allowing components such as PAs to operate in low-power modes whenever TX is not required. Improving PA efficiency is another priority given the substantial energy losses induced by high PAPR in 4G-LTE and 5G-NR signals. Optimizing waveforms to reduce PAPR can thus improve the actual energy efficiency of conventional PA architectures. In parallel, advanced PA architectures should be designed to maintain high efficiency under large OPBO. Furthermore, life-cycle considerations should be embedded directly into component design processes, especially to consider the production stage. The use of mineral and metal resources in BS components should therefore be reduced, particularly precious metals in electronic components and copper in cables. Ultimately, increases in hardware complexity should only be pursued when they offer clear potential for energy savings or life-cycle impact mitigation.

9.2.2 For mobile network operators

MNOs should prioritize reducing the environmental impacts of RANs during the use stage, as it dominates life-cycle impacts. This primarily requires minimizing total energy consumption, which is largely driven by the static power of BSs. In parallel, the environmental impacts of the electricity supply should be addressed as well. Compared to other supply options, the electricity grid in Belgium offers a balanced environmental footprint across impact categories. Nevertheless, efforts to reduce the impacts of electricity production should be accelerated at the country level. In contrast, recycling BS components at EoL has a limited influence on life-cycle impacts and should not be considered the only mitigation strategy.

Reducing RAN energy consumption entails preventing unnecessary capacity activation. Capacity should therefore be deployed selectively on BSs to match their operating conditions. This implies a paradigm shift from capacity-driven RAN deployment strategies toward sufficiency-oriented strategies. For instance, an efficient macrocell BS design identified for urban deployments in Belgium consists of combining one low-frequency band for coverage with one high-capacity band to handle peak traffic demand. While MIMO with multiple antennas and spatial layers increases flexibility and peak capacity, it also raises power consumption and should only be deployed when clearly justified by the operating conditions. Implementing effective PSSs is also highly relevant. Dynamic PSSs should generally be favored over fixed strategies, as they provide more stable QoS over time and deliver higher energy savings across varying traffic loads. Band sleep strategies offer a good balance between complexity and effectiveness, while layer sleep strategies can further reduce energy consumption in massive-MIMO bands, provided that coverage trade-offs are carefully managed.

Where feasible, network sharing should be pursued to minimize redundant infrastructure between MNOs. This can reduce the total number of active BSs while preserving or even improving service availability and territorial coverage. Without strong data traffic growth, further increasing the BS density would likely not

be necessary in Belgium. Thus, macrocell BSs should remain the default option, while microcell BSs should be reserved for dense traffic hotspots and specific environments where coverage is challenging. Finally, network efficiency improvements should be complemented by traffic stabilization mechanisms to counteract rebound effects. For instance, dynamic pricing schemes and QoS differentiation can help limit uncontrolled growth in data traffic and mitigate rebound effects.

9.2.3 For mobile network users

Mobile network users should first be aware that the aggregation of their individual data traffic demand directly influences the RAN deployment strategies and subsequent energy consumption and environmental impacts. Accordingly, mobile users can help stabilize overall data traffic by adopting usage patterns that reduce peak demand and unnecessary data transfers. This includes avoiding high-resolution streaming when not required, postponing large file transfers to off-peak hours, and favoring fixed access networks (e.g., Wi-Fi) when available. Accepting a limited rather than maximum data throughput during off-peak hours creates additional opportunities for PSSs, while smoothing traffic demand over the day prevents oversizing RAN capacity. More generally, usage patterns that sufficiently satisfy communication needs without demanding the highest QoS should be adopted.

9.2.4 For governance and decision-making processes

Governance and decision-making processes play a central role in steering the environmental transition of mobile Internet access. Informed decision-making first requires the use of appropriate metrics to assess RAN performance. For instance, energy intensity metrics normalized per unit of data traffic are highly sensitive to operating conditions, making them unsuitable for strategic planning. In contrast, metrics normalized per deployed capacity are more stable across operating conditions and more robust for country-level RAN assessments. Furthermore, transparency regarding RAN environmental impacts should be promoted to support informed decision-making by regulators, MNOs, and citizens. Beyond relative efficiency improvements, policy targets should be framed in absolute terms and aligned with global environmental constraints, explicitly accounting for rebound effects. In particular, the AESA methodology provides a structured approach to translate planetary boundaries into actionable region-specific targets for RANs. Importantly, the normative basis for setting targets should be explicitly stated and openly discussed, as it strongly influences the outcomes of the sustainability evaluations.

9.3 Limitations

A major limitation of this thesis is the lack of detail regarding the BS communication performance model and the practical implementation of the forward-inverse

network modeling. Although this reduces the transparency of certain results, these details were omitted to prioritize a more thorough presentation of both the BS power and life-cycle models, which constitute the primary contributions of this thesis. Other main limitations of this thesis can be discussed separately regarding model development and model applications.

9.3.1 In model development

Several limitations are related to the modeling approach of the integrated RAN model. First, the scope of the model does not cover emerging technologies, such as frequency bands beyond 6 GHz, small-cell and indoor BS architectures, and function virtualization. Similarly, the proposed model does not capture cell-free network typologies, nor cloud RAN and open RAN paradigms. The scope of the model is also limited to the RAN and excludes UEs, the core network, emerging non-terrestrial networks, and the rest of the Internet infrastructure. Second, the RAN model assumes regular and homogeneous BS deployments, which does not reflect the actual network heterogeneity and cannot capture site-specific characteristics. It also assumes homogeneous spatial UE distribution. While these assumptions are suitable for informing strategic planning, they are not appropriate for detailed network planning and BS placement optimization. Third, the proposed RAN model relies on a basic traffic model that does not differentiate by UE type (e.g., smartphones or IoT machines) or service (e.g., video streaming or text messaging). Finally, the assumed scheduling strategy allocates either all or none of the available physical resources of each subframe. While this strategy seems reasonable at first, more sophisticated scheduling policies are used in practice.

Additional limitations affect the BS power and life-cycle models. First, the relatively large empirical datasets used to calibrate these models do not capture the full diversity of BS component designs over time, among multiple manufacturers, or across different technologies. Consequently, the proposed models may lack technological, geographical, and temporal representativeness. Second, the DBB in the BS power model requires improvement and refinement, as it tends to overestimate power consumption. Third, the power consumption overhead and wake-up delay associated with PSSs are ignored in the BS power model, even though these factors may introduce non-negligible implementation trade-offs. Fourth, certain BS components and life-cycle stages require improvement and validation in the BS life-cycle model. This specifically includes the final component assembly, BS installation and deinstallation, component disassembly, and the disposal and recycling processes of all subcomponents. Finally, the background system of the BS life-cycle model is assumed to be static, even though IAFs should vary depending on factors such as the year or location of related foreground processes. However, theecoinvent database lacks the geographical and technological granularity necessary for parametric modeling of background processes. The cut-off approach in ecoinvent further limits the ability to perform detailed analyses of recycling processes.

9.3.2 In model applications

A general limitation in the investigated applications of the integrated RAN is their specific focus on Belgium. Thus, the results and key findings regarding efficient BS designs and prospective RAN deployments cannot be directly generalized to other regions. Another general limitation regarding model applications relates to the assessment of rebound effects, as the coupling between QoS and traffic demand is not directly represented within the integrated RAN model. Thus, rebound mechanisms are rather addressed by analyzing different traffic demands.

Specific limitations relate to the BS design evaluations. First, the evaluated BS designs are restricted to predetermined frequency band configurations, representative of deployments observed in Belgium. The results are therefore obtained from a limited design space that does not encompass all possible combinations of configuration variables. Second, these evaluations do not explore potential improvements of the default technological parameters of the integrated RAN model. Third, the examined daily traffic profile does not account for rare yet extreme peak loads or, in contrast, prolonged periods without traffic demand.

Other specific limitations relate to the prospective study of RAN deployments. First, the explored scenarios are neither predictive, exhaustive, nor proven to be optimal. Their realism is also affected by simplifying assumptions, including a fixed number of sites and subscriptions over 2020-2030, the exclusion of machine subscriptions, and a focus on macrocell BSs only. Second, the environmental impact assessment focuses solely on climate change through CO₂ emissions, neglecting potential burden shifting between planetary boundaries. Third, apart from electricity grid decarbonization, the background system is assumed to remain unchanged over the study period. Fourth, similar to the integrated RAN model, the study excludes other ICT products, as well as indirect effects in other sectors. Consequently, expanding the scope of the study could significantly alter its conclusions. Fifth, the outcomes of scenario evaluations through AESA strongly depend on the normative basis underlying the allocation process, as well as the quality and availability of the data used to estimate the associated scaling factors. Finally, this thesis leaves unanswered certain methodological questions related to future-oriented AESA (e.g., how should the remaining carbon budget be scaled down for specific future human activities?), due to the limited literature on this topic.

9.4 Perspectives for future research

The key findings and main limitations of this thesis ultimately serve to suggest perspectives for future research. The suggestions below successively address improvements to the proposed integrated RAN model, further applications of this model, and broader perspectives for future works.

9.4.1 Modeling improvements

Perspectives for modeling improvements include refining and improving certain parts of the proposed models, particularly those presenting the greatest uncertainty. To facilitate these developments, the integrated RAN model is planned to be published as an open-source software tool. Its modular and parametric modeling approach is expected to facilitate the implementation of upcoming improvements. For instance, numerical values of technological parameters can be adjusted without altering the model structure, and additional modules can be easily incorporated to represent other BS components. In addition, the technological scope of the model could be extended to represent emerging BS architectures, while environmental impact factors should be adjusted with the evolving technosphere, particularly with regard to electricity grid mixes. To maintain realistic models, continued model development should be based on additional primary data, whose open publication is strongly encouraged to ensure modeling transparency. Unfortunately, such transparency was not possible in this thesis due to confidentiality constraints. Furthermore, the communication performance assessment should examine additional QoS metrics, especially to analyze the effects of PSSs. For example, this could include UL coverage, system fairness, and cell-edge user throughput.

9.4.2 Further model applications

One perspective for further model applications is to optimize BS designs and RAN deployment strategies. Minimizing environmental impacts while maximizing QoS in BSs may involve optimizing the number of frequency bands, transmit power per band, bandwidth, number of spatial layers, PA architecture, network density, etc. This may also involve optimizing PSSs in the time, frequency, spatial, and power domains, including fine-tuning the resource activation thresholds. Future-oriented optimizations could search for potential RAN trajectories capable of achieving absolute decoupling between the provided QoS and environmental impacts. Such optimizations could also identify RAN deployment strategies and traffic demand trajectories that jointly meet environmental and social sustainability targets. Depending on the number of variables to be optimized, optimization algorithms such as gradient descent, genetic algorithms, or reinforcement learning could be employed. The weighting approach of LCIA methods could serve as an initial cost function to aggregate impact categories into a single environmental footprint score. Nevertheless, this thesis emphasizes the importance of clearly defining relevant and robust targets adapted to the desired goals before performing optimizations. This is particularly true for environmental sustainability, where the primary challenge lies in shifting research objectives from a relative to an absolute perspective before engaging in technical development and optimization.

9.4.3 Broader perspectives

For greater completeness, studies of RAN deployment strategies should also include the environmental impacts of UEs. This is especially important when existing technologies are phased out, as it helps to capture the direct induction, rebound, and obsolescence effects. Prospective studies in the medium to long term should also examine emerging and alternative technologies for mobile Internet access, such as non-terrestrial networks and neutral host networks, and include specific data traffic patterns from M2M, IoT, and AI-driven technologies. In addition, the proposed RAN model and associated BS models may serve as building blocks for studying larger product systems, such as entire ICT services. Studies of these services should include the core network, user devices, the Internet backbone, data centers, etc. Beyond direct effects, it would also be interesting to study the positive and negative indirect effects of mobile Internet access, potentially through a consequential approach. Such studies could include enabling effects on other sectors and systemic effects on the economy and society.

From a broader perspective, the challenge of achieving sustainable mobile Internet access should be addressed through interdisciplinary research, looking beyond the sole engineering perspective. This would first allow for a deeper exploration of the ethical and normative issues raised by the allocation of global environmental targets at the ICT, MNO or RAN levels. More importantly, it would allow for a more precise assessment of the actual human needs related to Internet access by questioning current usages and practices. This assessment could then provide a more accurate quantification of acceptable QoS requirements and thus identify a more reliable social foundation for RANs. Ultimately, interdisciplinary research should investigate the practical implementation of sufficiency-oriented strategies for both the ICT service providers and ICT users.

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From a personal standpoint, I believe this thesis provides valuable insights into overcoming the challenge of achieving sustainable mobile Internet access. Moreover, I hope it will inspire future engineering research to more broadly incorporate environmental sustainability considerations from an absolute perspective.

Appendices

A.1 Contributions of the European Union and Belgium to global warming

Figure A.1.1 indicates that the CO₂ emissions per person have remained stable worldwide since 1950. In contrast, territorial emissions per person have decreased significantly in the EU and Belgium since 2000, following an increase and stabilization over the past century. These trends suggest the implementation of effective territorial climate policies in Europe. However, consumption-based accounting reveals a less favorable trend in Belgium, where no significant reduction is observed today compared to 1990-2000. This underlines the need for additional climate policies that extend beyond the territory. Lastly, the current average territorial emissions per person in the EU are roughly the same as the global average, while the consumption-based emissions are approximately $\times 1.5$ higher. In Belgium, the current territorial and consumption-based CO₂ emissions per person are respectively about $\times 1.5$ and $\times 2.5$ higher than the global average.

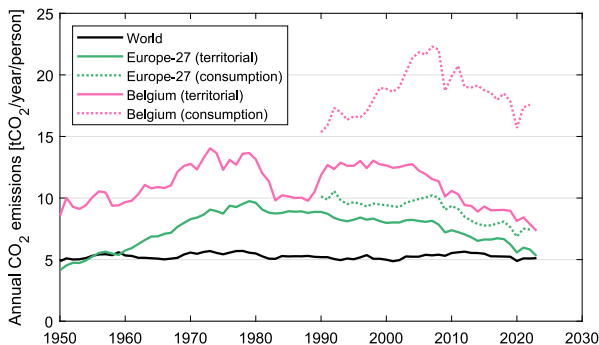


Fig. A.1.1 Annual territorial vs. consumption-based CO₂ emissions (fossil fuels and industry + land use, land-use change, and forestry) per person in European Union and in Belgium compared to the world average (data from [97]).

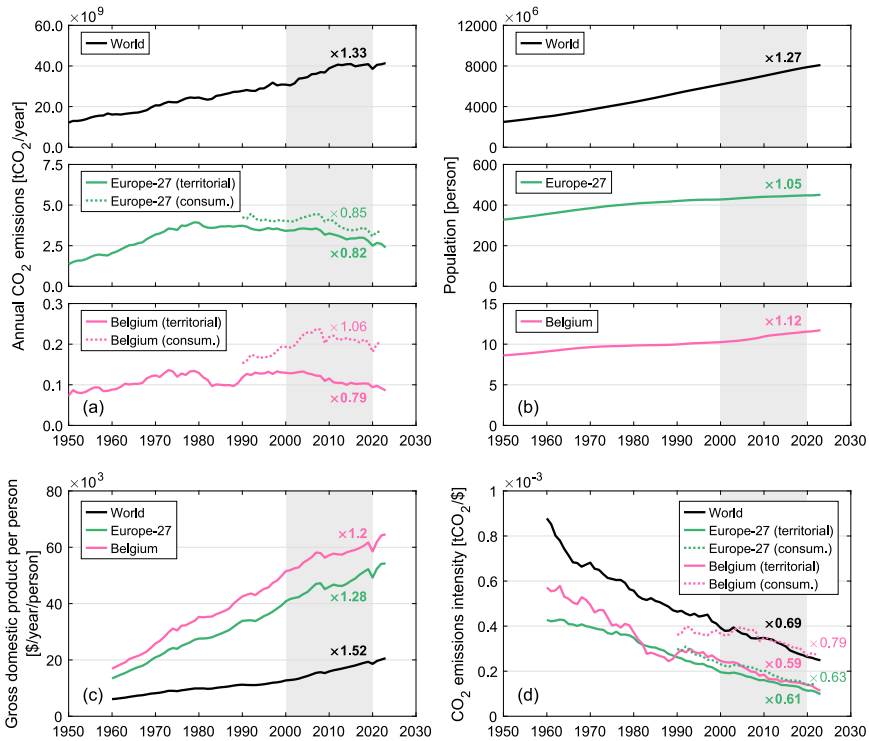


Fig. A.1.2 Illustration of the IPAT equation over time in the world, in the European Union and in Belgium: (a) environmental impact in annual territorial or consumption-based CO₂ emissions (fossil fuels and industry+land use, land-use change, and forestry), (b) human population, (c) human affluence in gross domestic product per person, and (d) technology factor in CO₂ emissions per unit of gross domestic product. Variation factors between 2000 and 2020 are indicated for each curve (data from [97, 264, 265]).

Figure A.1.2 shows the IPAT equation over time for annual CO₂ emissions worldwide, in the EU and in Belgium. GDP adjusted for purchasing power parity and inflation is used to represent the created value, expressed in constant 2021 international \$. For example, global annual CO₂ emissions increased ×1.33 over 2000-2020, corresponding to ×1.27 in population, ×1.52 in average GDP per person and ×0.69 in CO₂ per unit of GDP over the same period. Therefore, affluence is the main driver of the global rise in CO₂ emissions, along with population growth, while decarbonization partly offsets the overall increase. Over 2000-2020, the global economy has decarbonized at a slightly faster rate than both the EU and Belgium. Meanwhile, the global population and average global affluence have grown faster. Together, these factors have led to a reduction in territorial emissions in the EU and Belgium, while global CO₂ emissions have continued to rise.

A.2 Downlink vs. uplink: data traffic volume and physical resource load

Figure A.2.1 shows the ratio of UL to DL data traffic volume observed in on-site measurements at one BS site in 2023 for three 4G-LTE frequency bands. The estimated traffic-based ratio remains stable regardless of the data traffic level and frequency bands, indicating that approximately 90% of the mobile data traffic volume is generated in the DL (as $1/(1 + 0.11) \approx 0.9$). Then, Figure A.2.2 shows the ratio of hourly average UL to DL resource load observed in on-site measurements at one BS site in 2023 for three 4G-LTE and two 5G-NR frequency bands. The estimated load-based ratios remain stable regardless of the physical resource load, but differ between frequency bands, especially between 4G-LTE and 5G-NR bands. The estimated UL-to-DL ratios are also higher based on load than on traffic, which results from lower UL spectral efficiency.

Three reasons can explain the significantly higher load-based ratios for 5G-NR. First, the overall UL-to-DL data traffic ratio may differ for 5G-NR users compared to 4G-LTE users. Unfortunately, on-site measurements lack UL data traffic reports for 5G-NR bands, preventing these two bands from appearing in Figure A.2.1. Thus, the first reason cannot be validated. Second, TDD is implemented at 3.5 GHz, with approximately 75% of the subframes dedicated to DL and 25% to UL. Using this 3:1 ratio to adjust the estimated load-based ratio in Figure A.2.2(e) yields a corrected UL-to-DL ratio of $0.50/3 \approx 0.17$, which is closer to that of 4G-LTE cells (see Figure A.2.2(a)–(c)). This demonstrates the benefit of using TDD to balance the overall resource usage between DL and UL. Third, the BS scheduler likely prioritizes the UL resources of the 0.7 GHz band over the 3.5 GHz band due to its superior coverage. The coverage aspect is especially important for UL in 5G-NR. However, on-site measurements for the 5G-NR bands should be analyzed carefully because the 5G-NR load of the studied BS in 2023 was very low, making the measurements more sensitive to side effects.

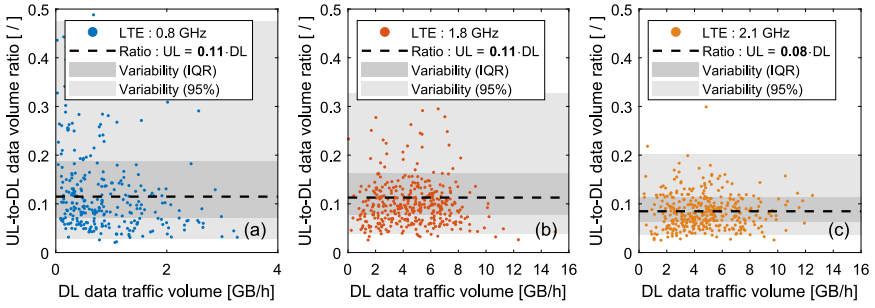


Fig. A.2.1 Ratio of uplink (UL) to downlink (DL) data traffic volume with respect to the hourly DL data traffic volume in 4G-LTE cells (from on-site measurements in 2023) at (a) 0.8 GHz, (b) 1.8 GHz, and (c) 2.1 GHz. Shaded areas represent the inter-quartile range (IQR) and 95% variability range around estimated ratios.

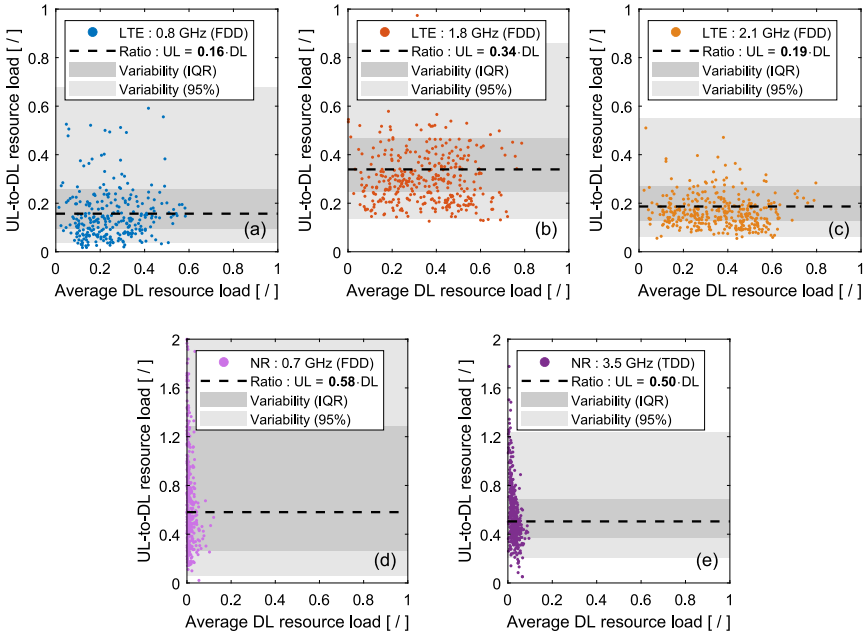


Fig. A.2.2 Ratio of uplink (UL) to downlink (DL) average resource load with respect to the hourly average DL resource load (from on-site measurements in 2023) in (a) 4G-LTE cells at 0.8 GHz, (b) 4G-LTE cells at 1.8 GHz, (c) 4G-LTE cells at 2.1 GHz, (d) 5G-NR cells at 0.7 GHz, and (e) 5G-NR cells at 3.5 GHz. (a)-(d) show frequency division duplex (FDD) cells, and (e) shows time division duplex (TDD) cells. Shaded areas represent the inter-quartile range (IQR) and 95% variability range around estimated ratios.

A.3 Validation of the base station communication performance model

As introduced in Section 4.5, model validation aims to qualitatively evaluate the accuracy of the proposed models. The validation process for the BS communication performance model follows the same strategy and validation set as for the BS power consumption model (see Section 5.7). However, it is also necessary to define the network, channel, and UE configurations to obtain results from the communication performance model. Thus, Table A.3.1 defines four typical network configurations in terms of model variables φ_{net} and φ_{chan} . The first three configurations – *Rural*, *Urban* and *Dense urban* – correspond to typical deployment areas for macro-cell BSs. The fourth configuration – *Micro* – corresponds to a typical microcell BS deployment. The associated BS and UE densities are derived from [JP1]. Assuming three MNOs with equal market shares, the UE density per MNO is 1/3 the population density. Next, Table A.3.2 defines two typical UE categories – *Category A* and *Category B* – in terms of configuration variables φ_{UE} . These two categories are respectively weighted at 0.8 and 0.2, and apply to all typical BS and network configurations. Note that Tables A.3.1 and A.3.2 only set the configuration variables that differ from the default values in Table 4.1.

Table A.3.1 Typical network and channel configurations

Variable	<i>Rural</i>	<i>Urban</i>	<i>Dense urban</i>	<i>Micro</i>
κ_{envi}	rural	suburban	urban	urban
ρ_{BS} [BS/km ²]	0.05	0.33	2	33
ρ_{UE} [UE/km ²]	50/3	750/3	10 ⁴ /3	10 ⁴ /3

Table A.3.2 Typical user equipment configurations

Variable	<i>Category A</i>	<i>Category B</i>
$\delta_{UE,cat}$ [/]	0.8	0.2
$N_{RX,UE}$ [#]	2	4

The first approach to model validation is to compare the SEs predicted by the model with the actual SEs observed in the validation set. For each typical frequency band, Figure A.3.1 compares the cumulative density function (CDF) of SE predictions with the actual SE of selected real-world cells. Figures A.3.1(a)-(d) examine the three sectors of a macrocell BS deployed in an urban environment, and Figure A.3.1(e) examines the single cell of two microcell BSs deployed in data traffic hotspots. These figures show CDFs for a one-week period in 2023, during which the hourly average load fluctuates. The CDFs describe the distribution of the link-level SE per data-carrying RE and spatial data layer, which are bounded by a minimum

and maximum SE imposed by the MCS of the communication protocols (based on quadrature amplitude modulation (QAM)). In 4G-LTE, the bounds are 0.4 and 5.5 bps/Hz/layer (see Figure A.3.1(a)-(c) and (e)), corresponding to 4-QAM 1/5 and 64-QAM 11/12 respectively [159]. In 5G-NR, the minimum bound remains the same, but the maximum bound extends to 7.3 bps/Hz/layer (see Figure A.3.1(d)), corresponding to 256-QAM 11/12 [160]. Since the CDFs apply only to REs carrying useful data, they do not capture UEs that are not covered by the frequency bands. Therefore, the CDFs only capture the SE delivered to part of the cell, but not the actual SE over the entire cell, as the latter should also include the uncovered UEs virtually experiencing 0 bps/Hz.

Figure A.3.1 first reveals variability in the CDF among cells within the same BS. This variability can be attributed to variations in the radio propagation environment around the BS, the level of inter-cell interference with neighboring BSs, the cell size, and the specific location of UEs within each cell. In microcells, Figure A.3.1(e) shows that > 60% of loaded REs use the higher MCS, suggesting very good channel quality due to the small cell size and interference-free environment. Figure A.3.1 also shows that the CDFs of SE predictions align decently with the CDFs of actual SEs in the validation set. Yet, the consistent shift to the left in the predicted CDFs indicates that the model is slightly pessimistic. This pessimistic trend can be explained by overlooking the ICIC, using generic radio channel models that do not represent the specific BS environment, and assuming homogeneous and regular RANs for small-scale assessments. Moreover, practical BSs do not appear to schedule UEs on the *Ma-N35* band if their channel quality would not allow an SE of at least 2 bps/Hz/layer (see Figure A.3.1(d)).

The second approach to model validation is to compare the predicted and observed SEs under both full-load and no-load conditions. For each typical frequency band and deployment area, Figure A.3.2 compares the full-load and no-load SEs predicted by the model and observed in all cells of the validation set. The full-load SE corresponds to the average SE over the cell when the network is fully loaded and experiences the highest level of inter-cell interference. Since this load level is rarely observed on an hourly basis in practice, the full-load SEs for the validation set are estimated by extrapolating the SE curve obtained for lower load levels. Conversely, the no-load SE corresponds to the average SE achievable in a cell when the network is empty and free of inter-cell interference. By nature, this SE is purely theoretical because no load means no data transmission and hence an absence of loaded REs. Consequently, for both predictions and actual observations, the no-load SE is estimated as the limit of the SE curve approaching zero load.

First, Figure A.3.2(a) shows the boxplot distributions of actual full-load and no-load SEs in each frequency band and deployment area. Full load SEs were not calculated for *Ma-N35* or *Mi-L18* because their actual loads in 2023 were too low for accurate extrapolation to full load. In general, the medians of full-load SEs are

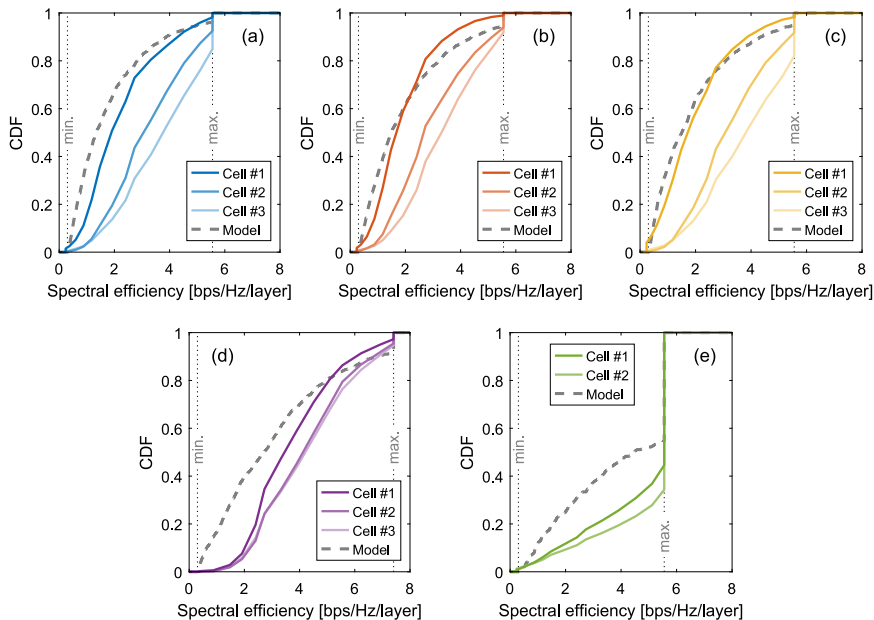


Fig. A.3.1 Cumulative density functions (CDFs) of the link-level spectral efficiency (SE) per data-carrying resource element and spatial data layer for (a) 4G-LTE macrocells at 0.8 GHz, (b) 4G-LTE macrocells at 1.8 GHz, (c) 4G-LTE macrocells at 2.6 GHz, (d) 5G-NR macrocells at 3.5 GHz, and (e) 4G-LTE microcells at 1.8 GHz. CDFs are bounded by the minimum and maximum SEs of the communication protocols. SE predictions by the base station communication performance model are compared with actual SEs of on-site measurements in the validation set, showing decent yet slightly pessimistic alignment.

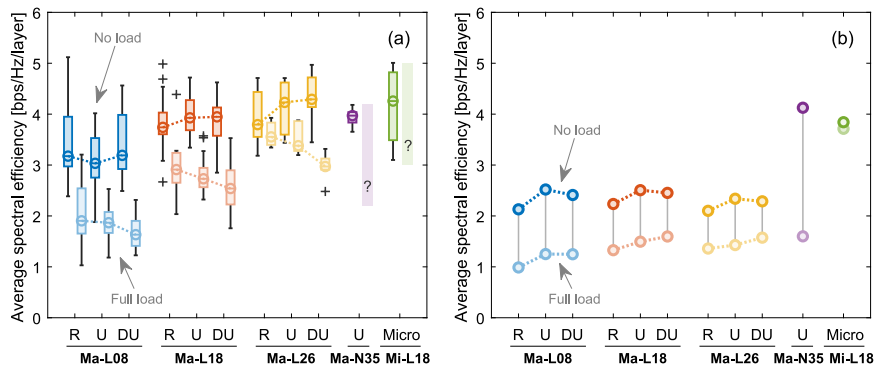


Fig. A.3.2 Full-load and no-load spectral efficiencies (SEs) in typical frequency band and deployment area: (a) boxplot distributions of actual SEs observed in all cells of the validation set, and (b) corresponding SEs predicted by the base station communication performance model. Predicted and observed trends are similar, but SE predictions are underestimated for traditional macrocell bands. (R=rural, U=urban, and DU=dense urban)

about 1 bps/Hz/layer lower than the medians of no-load SEs, which is statistically significant since their IQRs rarely overlap. This gap is explained by a deterioration in radio channel quality at high loads, primarily caused by higher inter-cell interference. In contrast, SE distributions are quite consistent across deployment areas for each band, suggesting that RANs in Belgium are well adapted to actual radio channels across the territory (e.g., via BS density and transmit power per band). Moreover, the average SE improves as the frequency carrier increases due to a selection bias in the calculations. Specifically, the average SE calculation only takes into account covered UEs (i.e., UEs with sufficiently good radio channels) and not all UEs located in the cell. This bias explains why the SE of the coverage band is lower than that of the capacity bands, as the primary purpose of *Ma-L08* is to connect all UEs, including those with poor radio channels.

Next, Figure A.3.2(b) shows the corresponding predicted full-load and no-load SEs in each frequency band and deployment area. For *Ma-L08*, *Ma-L18*, and *Ma-L26*, the full-load SEs are around 1 bps/Hz/layer lower than the no-load SEs, which aligns with the validation set. The predicted SEs are also consistent across deployment areas within each band, and the difference in SEs between these bands is minor. However, the predicted SEs for these bands are around 1-2 bps/Hz/layer lower than their actual SEs. This discrepancy supports the pessimistic tendency of the BS communication performance model. For *Ma-N35*, the predicted no-load SE around 4 bps/Hz/layer aligns with the observations and is $\times 2$ the predicted no-load SEs of the other macrocell bands. However, the validation set shows that the no-load SEs should be similar for all macrocell bands. Additionally, the predicted SE gap of *Ma-N35* is close to 3 bps/Hz/layer, higher than that of the other bands, but which cannot be validated. In the model, the higher SE of *Ma-N35* at low loads compared to the other bands is due to ABF with single-user MIMO because it achieves high beamforming gain, reducing inter-cell interference and improving SINR of all UEs. Yet, at high loads, ABF switches to multi-user MIMO, which then reduces transmit power per layer and restores some inter-cell interference, thereby strongly deteriorating SINR. Lastly, for *Mi-L18*, the no-load prediction aligns well with the observations. The model also predicts a very small gap between the full-load and no-load SEs for this band, but this cannot be validated.

Overall, the BS communication performance model roughly predicts SEs within the observed range of SEs in the validation set. The differences between full-load and no-load SEs, as well as SE variations across deployment areas, are also consistent. However, SE predictions are mostly underestimated for traditional macrocell bands, which gives bands featuring ABF excessive superiority. These discrepancies between actual observations and model predictions may stem from the use of generic radio channel models, the assumption of homogeneous and regular RANs at the small scale, the modeling of suboptimal scheduling strategies, and the overlooking of ICIC.

A.4 Extended analysis of the validation set

The validation set for both the BS communication performance and power consumption models consists of hourly on-site measurements taken over a one-week period in 2023. Since population density affects the number of potential UEs in the network, data traffic patterns, and the radio propagation environment [JP1] and [131–134], 32 operating BSs were randomly selected across Belgium to obtain a representative range of population densities. Moreover, the sampled BSs can be categorized by the typical configurations defined in Section 4.5. Thirty of these BSs are macrocell BSs with three sectors (i.e., $N_S = 3$), while the remaining two are omnidirectional microcell BSs (i.e., $N_S = 1$) deployed in data traffic hotspots.

For macrocell BSs in the validation set, Figure A.4.1 plots the BS density and the maximum number of connected users per BS according to the population density at the BS location, ranging from 20 to 2×10^4 pers/km². At short time scales, it is important to note that only a small fraction of connected users are active simultaneously (i.e., transferring data in the DL and UL). The selected BSs are also

Table A.4.1 Deployment areas for macrocell base stations in the validation set

Characteristic		Rural	Urban	Dense urban
Population density [pers/km ²]	typical (range)	50 (0–250)	750 (250–3000)	10 ⁴ (>3000)
Related areas in [JP1] and [131–134]		Wilderness & Rural	Suburban & Urban	Dense urban & Super dense urban

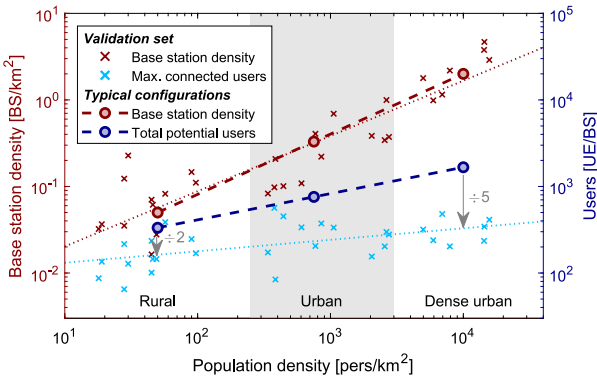


Fig. A.4.1 Base station density (left axis) and maximum number of connected users (right axis) vs. population density for macrocell base stations in the validation set. Base station density (left axis) and total number of potential users (right axis) are also shown for the three typical network configurations. The base station density increases with population density to ensure a limited increase in the number of users per base station.

grouped into three deployment areas – rural, urban, and dense urban – whose key characteristics are provided in Table A.4.1. For these three deployment areas, Figure A.4.1 depicts the typical BS density and total number of potential users per BS. These values are estimated based on the characteristics in Table A.4.1 under the assumption of three identical MNOs with the same market shares.

In Figure A.4.1, the BS density increases by approximately two orders of magnitude from rural to dense urban areas, while the maximum number of connected users per BS only doubles. This shows that increasing the density of BSs across deployment areas prevents the maximum number of connected users per BS from increasing significantly. However, the total number of potential users per BS is $\times 2$ and $\times 5$ the maximum number of connected users per BS in rural and dense urban areas, respectively. These discrepancies occur because population density does not exactly reflect the actual user density, especially when market penetration is $< 100\%$. Additionally, not all potential users connect to the mobile network simultaneously, even during peak hours.

Next, Figure A.4.2 shows the boxplot distribution of the total transmit power density per cell at full load for each typical configuration in the validation set. In rural and urban areas, the transmit power for all *Ma-L08* cells operating on the coverage band is configured at 80 W per cell. In dense urban areas, however, this varies from 10 to 80 W, with a median value of ~ 45 W. The power densities of *Ma-L18* and *Ma-L26* cells are generally $1/2$ that of the *Ma-L08* cells, but with $\times 2$ the bandwidth, resulting in a similar total transmit power per cell. However, the configuration of transmit power per cell is more variable for these cells. The transmit power density for *Ma-N35* and *Mi-L18* is lower, at ~ 1 W/MHz. The

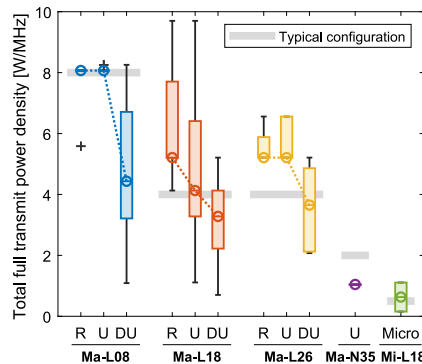


Fig. A.4.2 Boxplot distribution of total full transmit power density for base stations in the validation set, categorized by typical configurations. Power density is highest for *Ma-L08*, lowest for *Ma-N35* and *Mi-L18*, and decreases with population density. Typical configurations align with the validation set. (R=rural, U=urban, and DU=dense urban)

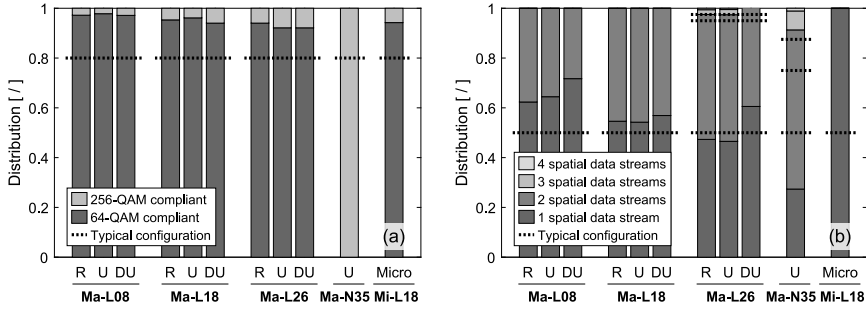


Fig. A.4.3 Stacked distributions for base stations in the validation set, categorized by typical configurations, of (a) user equipment configurations, and (b) achieved number of spatial data streams. Most user equipments are 64-QAM compliant, except in *Ma-N35* cells where they are all 256-QAM compliant. The spatial layer decorrelation probability of 0.5 appears to be realistic. (R=rural, U=urban, and DU=dense urban)

proposed typical BS configurations align well with observed cells in the validation set, except for the *Ma-N35* configuration. In that case, the choice of 2 W/MHz instead of 1 W/MHz is justified by the fact that the three cells observed in this configuration supports two 100 MHz carriers for two MNOs, resulting in an overall 200 W per cell. Yet, the corresponding typical BS configuration assumes a single 100 MHz carrier, hence doubling the transmit power density.

Regarding the technical capabilities of UEs, Figure A.4.3(a) shows the distribution of 64-QAM and 256-QAM compliant UEs observed for the BSs in the validation set. In 4G-LTE cells, >90% of UEs are only 64-QAM compliant, whereas all UEs are 256-QAM compliant in 5G-NR cells. Thus, QAM compliance may reflect the UE generation and their communication capabilities. Assuming that the number of antennas supported by a UE also reflects its communication capability, the 80:20 distribution of typical UE categories considered in Chapters 7 and 8 and Appendix A.3 appears realistic yet more optimistic than empirical observations. Then, Figure A.4.3(b) shows the distribution of the achieved number of spatial data streams (i.e., the channel rank) observed for the BSs in the validation set. The maximum number of achievable spatial data streams is limited by the minimum number of transmit and receive antennas or the number of spatial data layers. Therefore, *Ma-L08*, *Ma-L18* and *Mi-L18* configurations offer a maximum of 2 spatial data streams, whereas *Ma-L26* offers a maximum of 4 streams and *Ma-N35* offers a maximum of 8 streams. However, the maximum number of 4 streams can only be achieved by UEs with 4 antennas, which are assumed to correspond to 256-QAM compliant UEs. The limited share of such UEs explains the low utilization of 3 and 4 spatial data streams in *Ma-L26*. In addition, achieving an independent spatial data stream requires decorrelation of the associated spatial data layer from the

other layers. In the integrated RAN model, this aspect is modeled via the channel configuration variable δ_{decorr} . Figure A.4.3(b) shows that using the default value $\delta_{decorr} = 0.5$ is realistic but not perfect.

BSs in the validation set can also be used to study the physical resource usage in 2023. For each typical configuration, Figure A.4.4(a) shows the boxplot distributions of the average physical resource load. Similarly, Figure A.4.4(b) shows the boxplot distributions of the average physical resource load during the busiest hour, namely the hourly maximum physical resource load. In general, the maximum load during the busiest hour is roughly $\times 2$ the average load. For each frequency band, average and maximum loads are higher for BSs deployed in more densely populated areas. This reflects more intense usage of these BSs, which is consistent with their higher number of potential users (see Figure A.4.1). Since *Ma-L08* cells operate on the coverage band, they are the busiest with a median load of 20-40%. In contrast, *Ma-N35* and *Mi-L18* cells are significantly less busy, with a median load $< 10\%$. However, this observation is not very robust because the validation set contains only three *Ma-N35* cells and two *Mi-L18* cells. During the busiest hour, some *Ma-L08* cells reach an average load of $> 90\%$ in urban and dense urban areas, suggesting these cells are nearly saturated. Therefore, additional capacity bands are needed to prevent saturation of the associated BSs. In addition, Figure A.4.4(c) shows the boxplot distributions of average physical resource availability. An availability < 1 indicates the implementation of PSSs that deactivate part of the resources, usually during low-traffic periods. Figure A.4.4(c) shows that neither the coverage band nor are the microcells are deactivated. Conversely, the *Ma-L18* and *Ma-L26* cells are frequently deactivated, particularly in rural areas where their median availability is $< 50\%$. Surprisingly, the *Ma-N35* cells are rarely deactivated despite a very low load. However, this specific observation cannot be directly generalized, as previously mentioned.

Finally, Figure A.4.5 shows the maximum load and average availability of all physical resources for the BSs in the validation set, plotted against their average physical resource load. It shows that the average load of an entire BS during the busiest hour is typically $\times 1.67$ its average load. In general, the average BS resource availability follows the same trend, with a margin of approximately $+30\%$. For instance, the physical resources of a BS with an average load of 20% are available at $1.67 \cdot 20 + 30 \approx 60\%$ on average. Thus, a BS with an average load of $> 40\%$ remains always fully available.

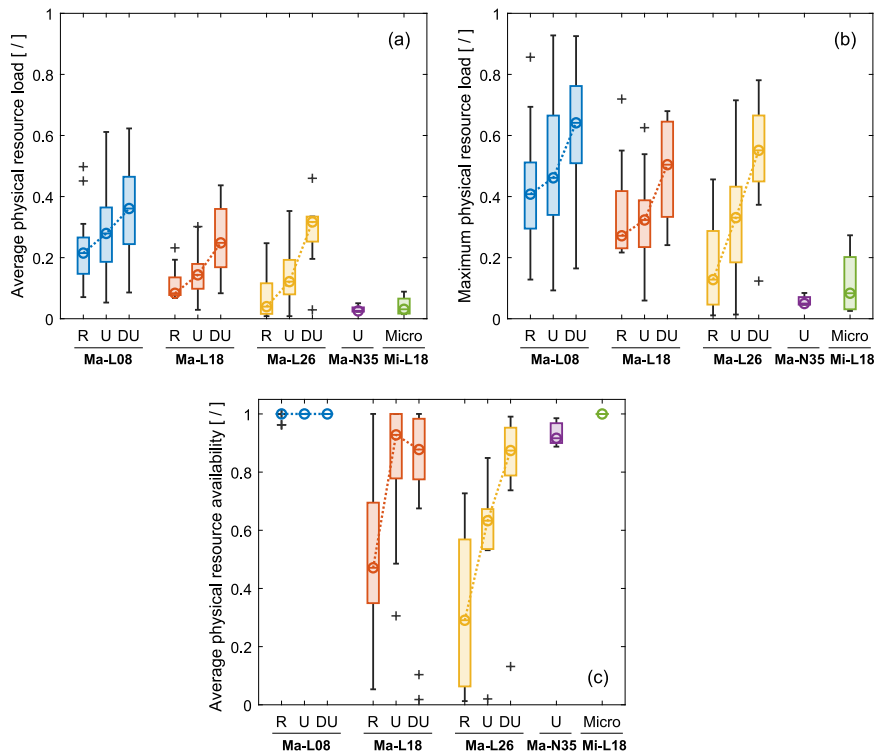


Fig. A.4.4 Boxplot distributions for base stations in the validation set, categorized by typical configurations, of (a) average physical resource load, (b) hourly maximum physical resource load, and (c) average physical resource availability. Load is highest for *Ma-L08* and lowest for *Ma-L08* and *Ma-L08*. *Ma-L08* is always fully available. Load and availability increase with population density. (R=rural, U=urban, and DU=dense urban)

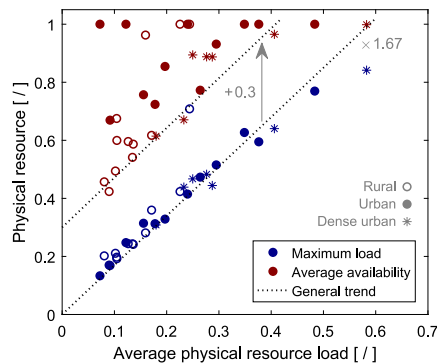


Fig. A.4.5 Hourly maximum physical resource load and average physical resource availability vs. average physical resource load for base stations in the validation set. General trends are consistent across observed base stations.

A.5 Physical resource load levels per subframe

The load allocation strategy across the resource grid in the time and frequency domains is crucial for modeling network traffic and BS power consumption in the integrated network model. Based on on-site measurements of a macro BS, Figure A.5.1 shows the distribution of physical resource load levels per subframe for several 4G-LTE cells across three frequency bands over the course of one week in 2023. For each frequency band, the subfigures illustrate the proportion of time that subframes experience a given load level, categorized by decile intervals. For instance, Figure A.5.1(a) shows that, in all cells at 0.8 GHz, approximately 7% of subframes experience a load ranging from 10% to 20%. Additionally, Figure A.5.1 shows that, out of ten load levels, only three are predominantly used by the BS across the three examined frequency bands: very low to no load ($\leq 10\%$), low load (10–20%), and very high to full load ($> 90\%$).

Ignoring the low load level of 10–20%, the load allocation on the resource grid behaves primarily as an all-or-nothing strategy, exhibiting on/off scheduling approach. Thus, BS either does not transfer any data traffic, leaving the subframes empty, or it loads its subframes to maximum capacity when there is data traffic. Therefore, practical schedulers seem to favor maximum bandwidth utilization for minimum time resource utilization. As a result, the throughput fluctuates significantly at the subframe time scale: it is either full-capacity throughput when subframes are active, or zero or near-zero throughput otherwise.

This behavior is consistent with bursty packet-based Internet data traffic patterns [12, 13, 266]. It contrasts with legacy wireless communications systems that aimed to guarantee continuous fixed throughput for each user connected to the mobile network. This on/off behavior justifies the simplification of the traffic and BS models in the integrated network model, assuming that all PRUs available in a cell are loaded when a subframe is loaded. This scheduling strategy hence favors the DTX mode, enabling the implementation of time-domain PSSs. Unfortunately, on-site measurements lack reports on the distribution of load levels per subframe for 5G-NR bands. Consequently, the same scheduling strategy cannot be confirmed for 5G-NR, even though the simplifying on/off assumption is also adopted for these bands in the integrated network model.

Furthermore, the proportion of time that cells operate at a low load level (10–20%) appears consistent at around 7% across all cells. However, higher inter-cell variation is observed between bands and within bands. This suggests that the low load level may be associated with a resource overhead of the communication protocol (e.g., primary and secondary synchronization signals). Then, Figure A.5.2 shows the hourly distribution of load levels per subframe over a one-week period in 2023 for one 4G-LTE cell at 0.8 GHz. For instance, it shows that during the busiest hour on the Wednesday, 7% of subframes were loaded at 10–20%, 30% were loaded at $> 90\%$, and 10% were loaded at 20–80%. The remaining subframes were loaded

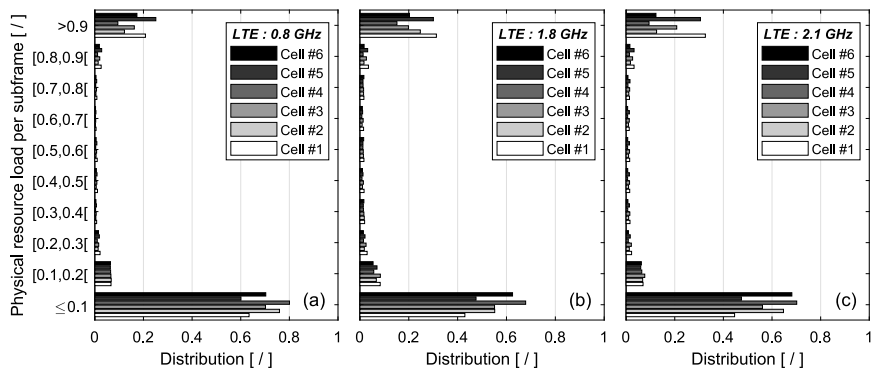


Fig. A.5.1 Distribution of physical resource load levels per subframe over a one-week period in 2023 for several 4G-LTE cells at: (a) 0.8 GHz, (b) 1.8 GHz, and (c) 2.1 GHz (from on-site measurements).

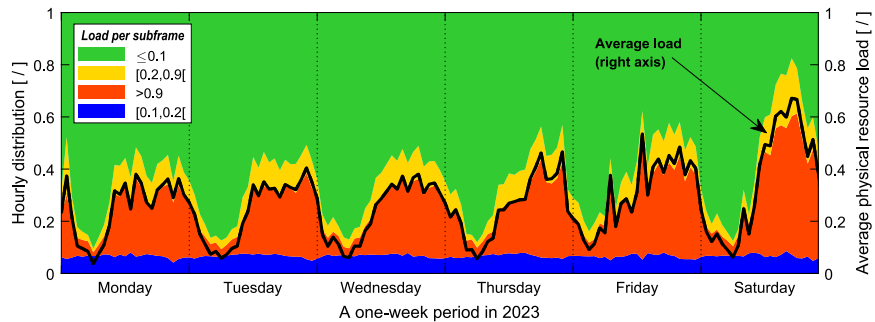


Fig. A.5.2 Stacked hourly distribution of physical resource load levels per subframe (left axis) and hourly average physical resource load (right axis) over a one-week period in 2023 for one 4G-LTE cell at 0.8 GHz (from on-site measurements).

at $\leq 10\%$. Notably, the proportion of time that subframes spend at the low load level remains stable over time, at approximately 7%, supporting the assumption that this load level is due to a static protocol overhead. In contrast, the share of the nearly full-load level ($> 90\%$) fluctuates significantly over time and is closely correlated with the hourly average resource load. Intermediate load levels, grouped into a single 20-90% category, are only used to a lesser extent.

A.6 Impact assessment factors: Abiotic resource depletion potential

Figure A.6.1 shows the IAFs for the “resource use – minerals and metals” impact category through the ADP indicator. Compared with GWP, the impact of using copper is much more pronounced, e.g., in PSU power converters, RU filters, power cables, but also in the transmission and distribution networks of electrical grids. In contrast, the use of fossil polymers and the combustion of fossil fuels are negligible for ADP. Another impact category covers separately the use of fossil resources.

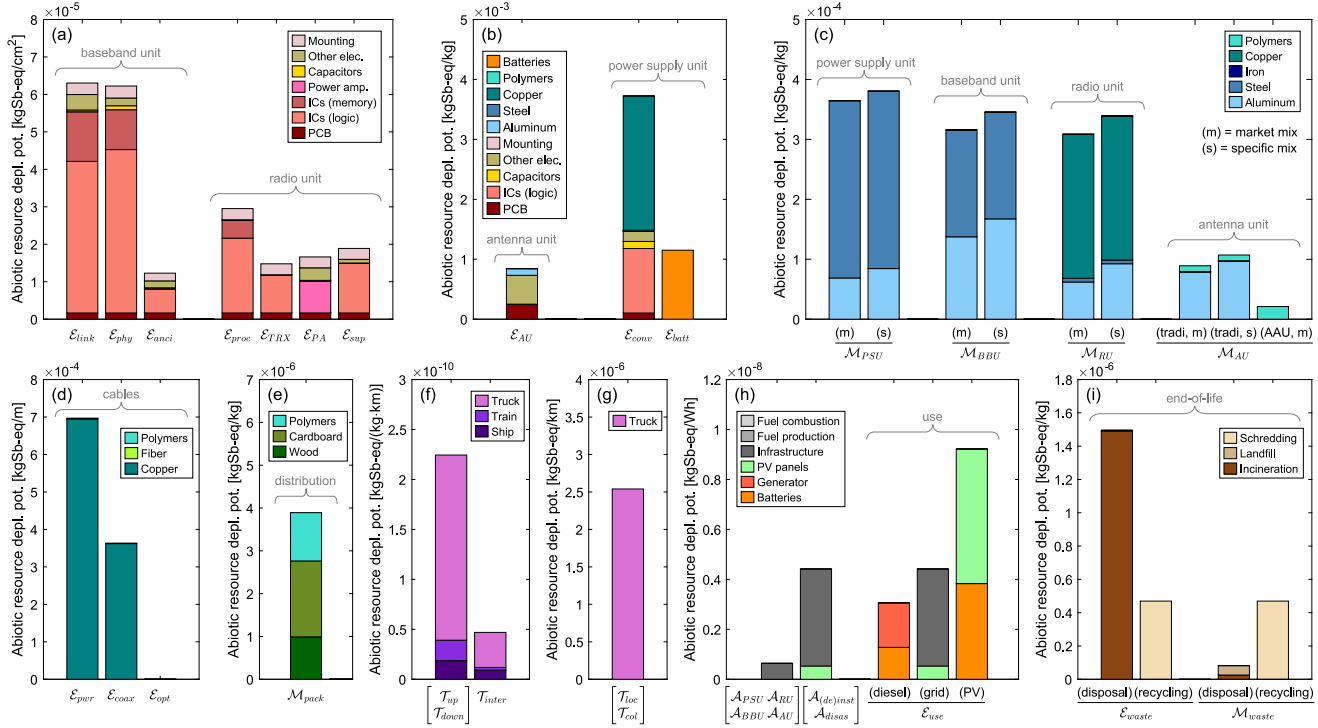


Fig. A.6.1 Abiotic resource depletion potential for all foreground processes of the base station life-cycle model: (a) printed circuit board assembly production, (b) other electronic production, (c) mechanical structure production, (d) cable production, (e) packaging production and disposal, (f) freight transport, (g) local transport, (h) electricity consumption, and (i) waste management routes. Some impact assessment factors apply to multiple foreground processes [*in brackets*], while different impact assessment factors can be assigned to a single process depending on the model options (*in parentheses*).

A.7 Extended analysis of the prospective scenarios

Figure A.7.1 illustrates the data traffic volume breakdown per frequency band for the *base* scenarios of the five RAN deployment strategies from 2020 to 2030. The figure also illustrates the total RAN capacity and availability in terms of data traffic volume. Figure A.7.1(a) shows that the *Do nothing* strategy only uses 4G-LTE bands, with most traffic transferred via the 1.8 GHz band. As total traffic demand approaches total traffic capacity, a demand gap appears in 2028 between demanded and actually transferred traffic volume. This indicates that the *linear* traffic demand trajectory is not feasible with this strategy. Next, Figures A.7.1(b) and A.7.1(c) are identical because the *Business as usual* and *Network sharing* strategies deploy the same physical resources in the RANs. For these two strategies, most traffic is transferred via the 5G-NR band at 3.5 GHz after 2026. With the *4G shutdown* strategy, Figure A.7.1(d) shows that all traffic is transferred via the 5G-NR bands only from 2027 onwards. Similarly, Figure A.7.1(e) shows that, after 2025, all traffic is transferred via custom bands. In the latter case, RANs are designed to provide a level of traffic volume availability that closely follows the data traffic demand.

Furthermore, Figure A.7.2 illustrates the breakdown of annual energy consumption per frequency band for the *base* scenarios of the five RAN deployment strategies from 2020 to 2030. Figure A.7.2(a) shows that the energy consumption of the *Do nothing* strategy comes solely from 4G-LTE bands, particularly the 0.8 and 1.8 GHz bands. Then, Figure A.7.2(b) shows that the *Business as usual* strategy adds the energy consumption of new bands to that of previously deployed bands. In this case, the energy consumption of 4G-LTE bands remains fairly stable over time. Figure A.7.2(c) shows a similar trajectory with the *Network sharing* strategy, although the total energy consumption is slightly lower thanks to the mutualization of BS components by MNOs. With the *4G shutdown* strategy, Figure A.7.2(d) shows that the total RAN energy consumption is maintained fairly stable over time by gradually replacing 4G-LTE bands with 5G-NR bands. Finally, Figure A.7.2(e) shows that the *Post-growth* strategy replaces the energy consumption of 4G-LTE bands with that of custom bands. Unlike the previous strategies, the total RAN energy consumption decreases over time with the *Post-growth* strategy thanks to custom BS configurations designed for sufficiency.

Figure A.7.2 also illustrates the breakdown of annual CO₂ emissions per life-cycle stage. Since the use stage dominates the CO₂ emissions of RANs, their annual trajectories mirror the annual energy consumption trajectories. One notable difference comes from the decarbonization of the electricity grid, which drives down CO₂ emissions from the use stage. Another difference arises from the allocation of emissions from the production, distribution, and EoL stages entirely to the years when the BS components are installed or deinstalled. This results in emission peaks in 2021, 2023, 2025, and 2027. In Figure A.7.2(f), the *Do nothing* strategy only in-

volves the use stage since no BS components are installed or uninstalled. Comparing Figures A.7.2(g) and A.7.2(h) also shows that the *Business as usual* strategy requires producing more BS components because no components are shared between MNOs. In contrast, the *Network sharing* strategy replaces all BS components that are not shared between MNOs, which must then be processed at EoL. Then, Figure A.7.2(i) shows that the *4G shutdown* strategy requires producing fewer BS components because components supporting 4G-LTE bands are not replaced. Finally, the *Post-growth* strategy depicted in Figure A.7.2(j) is the only one that follows the SBTi trajectory established by the ITU for mobile networks.

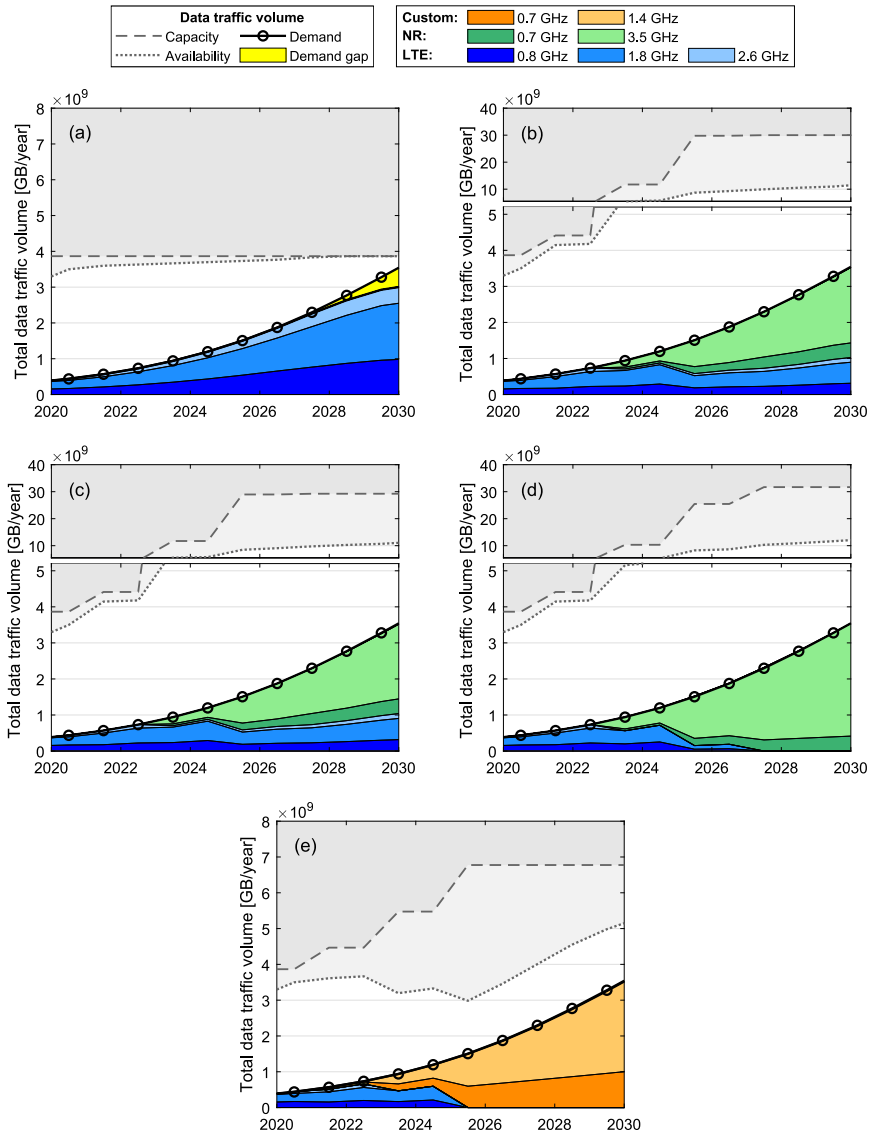


Fig. A.7.1 Data traffic volume breakdown per frequency band from 2020 to 2030 for the base scenarios of (a) *Do nothing*, (b) *Business as usual*, (c) *Network sharing*, (d) *4G shutdown*, and (e) *Post-growth* strategies. The *Do nothing* strategy results in a demand gap. The breakdown is identical with the *Business as usual* and *Network sharing* strategies. With the *4G shutdown* strategy, the 5G-NR bands transfer all the data traffic after 2027. With the *Post-growth* strategy, the custom bands transfer all the data traffic after 2026.

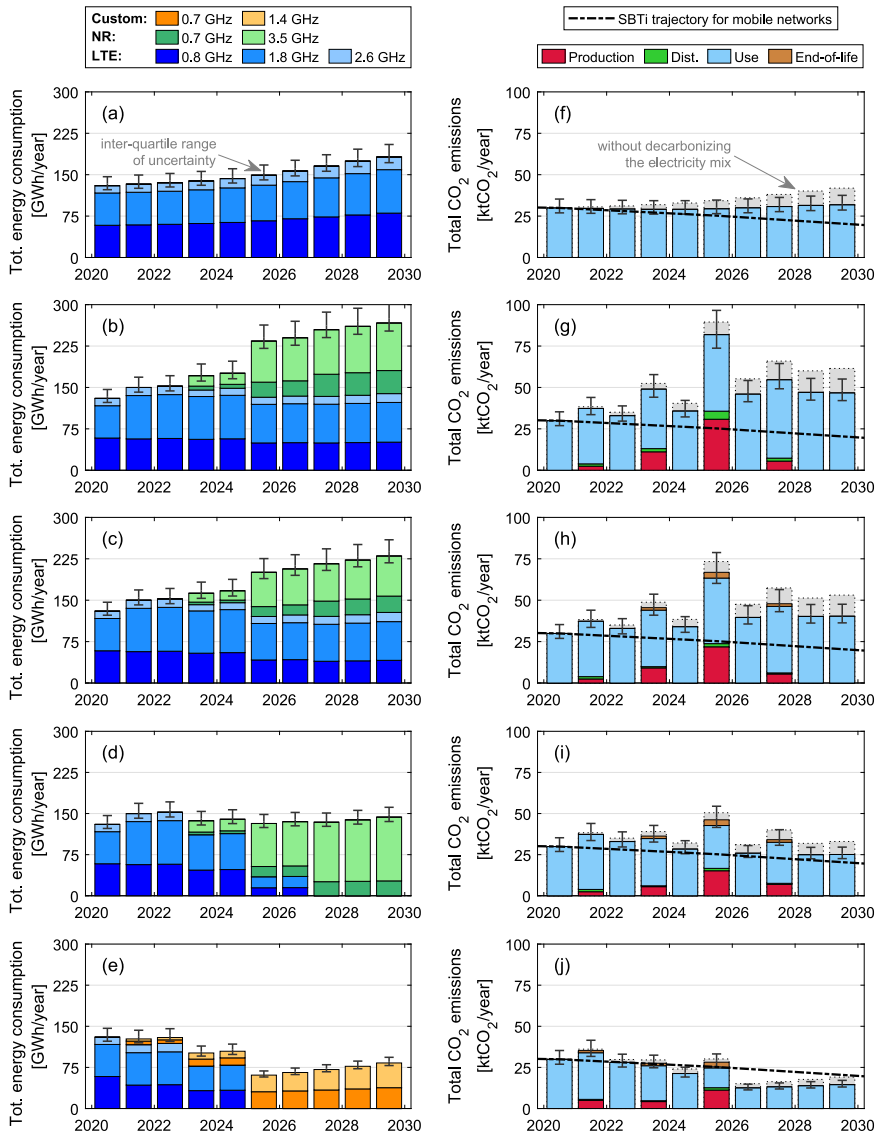


Fig. A.7.2 Annual energy consumption breakdown per frequency band from 2020 to 2030 for the base scenarios of (a) *Do nothing*, (b) *Business as usual*, (c) *Network sharing*, (d) *4G shutdown*, and (e) *Post-growth* strategies, and corresponding annual CO₂ emissions breakdown per life-cycle stage for the (f) *Do nothing*, (g) *Business as usual*, (h) *Network sharing*, (i) *4G shutdown*, and (j) *Post-growth* strategies. CO₂ emissions trajectories reflect the energy consumption trajectories, except that the electricity grid decarbonization reduces use-stage emissions, and emissions from production, distribution, and end-of-life stages are entirely allocated to the years when base station components are installed or uninstalled.

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