UCLouvain
Institute for Information
and Communication Technologies,
Electronics and Applied Mathematics

Environmental Perspectives and Limits for the Internet of Things in the Anthropocene: Going Beyond Systematic Life-Cycle Assessment

Thibault Pirson

Thesis submitted in partial fulfillment
of the requirements for the degree of
Docteur en sciences de l'ingénieur et technologie

Dissertation committee:

Prof.	David Bol	*Advisor*	UCLouvain, Belgium
Prof.	Laurent Francis	*President*	UCLouvain, Belgium
Prof.	Denis Flandre	*Secretary*	UCLouvain, Belgium
Dr.	Marie Garcia Bardon		imec, Belgium
Dr.	Lutz Stobbe		IZM Fraunhofer, Germany
Dr.	Guillaume Carnino		UTC, France

Contents

Abstract

SINCE a few decades, the development of technologies is moving forward at a frantic rate. In particular, the rapid development of Information and Communication Technologies (ICT) has deeply shaped our modern societies through Internet, personal computers, cloud computing, mobile communication, smartphones, and more recently the Internet of Things (IoT). The IoT aims at connecting every physical object to the cloud, everywhere, and at all time. In 2030, the number of IoT devices worldwide is expected to reach up to 200 billions, hence becoming the fastest-growing part of ICT. Electronic components will be incorporated into everyday appliances to support ubiquitous computing, transforming them into *smart* systems connected over the Internet and mobile networks. Emerging technologies such as IoT are strongly orienting innovation in academia and industry, supported by significant financial investments and digitalization policies. In fact, these technologies are frequently presented as a way to make our lives more comfortable and to reduce the environmental footprint of our societies through their ability to connect, monitor, and optimize complex systems in real time. This applies for numerous applications in the field of city and building management, farming, and healthcare for instance.

However in the meantime, the socio-technical system is generally moving further away from a state of environmental sustainability and stability. In fact, humanity has exceeded six planetary boundaries out of nine in less than 200 years, including climate change and biosphere integrity. The pressure of anthropogenic activities has become the main driver of global environmental change to the extent that according to geologists and environmental chemists, it marks the beginning of a new geological epoch called the *Anthropocene*. In particular, the ever-increasing worldwide greenhouse gas (GHG) emissions leading to global warming put the Earth system (and humankind) under serious risks due to climate change effects such as severe droughts, heatwaves and rainfalls. Given the critical implications of threatening environmental sustainability at a global scale, every activity of humanity is called to urgently decrease its environmental pressure. This starts with a necessary sharp decrease of GHG emissions, as supported by reports from the

Intergovernmental Panel on Climate Change (IPCC) since the 1990's. The ICT is hence also called to reduce its carbon footprint. However, current estimates do not include the footprint of IoT devices, even if ICT end-devices already represent a significant share of the overall ICT footprint. The massive ongoing deployment of IoT devices therefore raises important environmental sustainability concerns, further supported by the fact that the environmental impacts of IoT were mostly overlooked when we started working on this topic.

This thesis therefore aims at improving the understanding of the environmental impacts associated to IoT devices. It is organized in two different but complementary parts. The first part is mainly based on a bottom-up approach and argues for the need of systematic environmental evaluation through life-cycle assessment (LCA) in the context of the IoT, as it is far from being the case today. We propose concrete ways to foster it in practice, largely supported by quantitative analyses. In particular, we introduce the concept of *hardware profiles* to address the challenge of the high heterogeneity inherent to IoT devices and we develop a quantitative framework to streamline the evaluation of the carbon footprint due to the production of a wide variety of IoT devices. Then, we dig further into the environmental footprint of integrated circuits production, as they are a key component of IoT devices. We provide the first extensive literature review on the topic, supported by qualitative and quantitative analyses. Finally, we carry out a full-scope multi-indicator LCA of a real-life IoT solution for smart public lighting deployed in Belgium, which is helpful to highlight the trade-offs between streamlined and full LCA approaches in the field of IoT. The second part of this thesis rather takes a top-down approach to provide global environmental perspectives. In particular, we build upon the work conducted in the first part to illustrate that solely relying on systematic LCA is not sufficient to foster absolute environmental sustainability. Then, we investigate how the massive IoT deployment would be impeded if we consider environmental limits such as planetary boundaries or Paris Agreements targets. In this context, we identify *backcasting* studies as a well-suited approach to identify IoT solutions that are relevant to be deployed, or conversely, the ones that should be avoided or strongly discouraged with respect to environmental limits. This supports an important paradigm shift that departs from the conventional approach exclusively focusing on the relative environmental improvements of individual IoT solutions through eco-design. Taken together, these two parts propose concrete answers to the research question **to which extent could the systematic LCA of IoT devices help keeping the IoT footprint within environmental limits?**

Author's publication list

Related journal papers

JP1. T. Pirson and D. Bol, "Assessing the embodied carbon footprint of IoT edge devices with a bottom-up life-cycle approach" *Journal of Cleaner Production*, vol. 322, p. 128966, Nov. 2021.
DOI: 10.1016/j.jclepro.2021.128966

JP2. T. Pirson, T. Delhaye, A. Pip, G. Le Brun, J-P. Raskin, and D. Bol, "The Environmental Footprint of IC Production: Review, Analysis and Lessons from Historical Trends" *IEEE Transactions on Semiconductor Manufacturing*, vol.36, no. 1, pp. 56–67, Feb. 2023.
DOI: 10.1109/TSM.2022.3228311

JP3. M. Gonzalez, P. Xu, R. Dekimpe, M. Schramme, I. Stupia, T. Pirson, and D. Bol, "Technical and Ecological Limits of 2.45-GHz Wireless Power Transfer for Battery-Less Sensors", *IEEE Internet of Things Journal*, Early Access, Apr. 2023.
DOI: JIOT.2023.3263976

JP4. G. Roussilhe, T. Pirson, M. Xhonneux, and D. Bol, "From Silicon Shield to Carbon Lock-in? The Environmental Footprint of Electronic Components Manufacturing in Taiwan (2015-2020)", *arXiv preprint*, Sep. 2022, (submitted to Journal of Industrial Ecology).
arXiv:2209.12523

Related conference papers

CP1. T. Pirson and D. Bol, "Evaluating the (ir)relevance of IoT solutions with respect to environmental limits based on LCA and backcasting studies. The case study of smart public lighting in Wallonia, Belgium (2020-2050)", in "LIMITS '23: Workshop on Computing within Limits", Jun. 2023.
DOI: 10.21428/bf6fb269.6af396ff

CP2. T. Pirson, T. Delhaye, A. Pip, G. Le Brun, J-P. Raskin, and D. Bol, "The Environmental Footprint of IC Production: Meta-Analysis and Historical Trends", in *ESSDERC 2022-IEEE 52nd European Solid-State Device Research Conference (ESSDERC)*, Sep. 2022, pp. 352–355.
DOI: 10.1109/ESSDERC55479.2022.9947198

CP3. P. Maistriaux, T. Pirson, M. Schramme, J. Louveaux, and D. Bol, "Modeling the Carbon Footprint of Battery-Powered IoT Sensor Nodes for Environmental-Monitoring Applications", in *Proceedings of the 12th International Conference on the Internet of Things*, Nov. 2022, pp. 9–16.
DOI: 10.1145/3567445.3567448

CP4. D. Bol, T. Pirson, and R. Dekimpe, "Moore's Law and ICT Innovation in the Anthropocene", in *Proc. of the IEEE 2021 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, Feb. 2021, pp. 19-24.
DOI: 10.23919/DATE51398.2021.9474110

Related book chapters

BC1. T. Pirson, G. Le Brun, E. Quisbert-Trujillo, T. Ernst, J-P. Raskin, and D. Bol, "Towards life cycle thinking and judicious ecodesign for the Internet-of-Things (IoT): current practices and perspectives", **in press**.

Related opinion papers

OP1. N. Moreau, T. Pirson, G. Le Brun, T. Delhaye, G. Sandu, A. Paris, D. Bol, and J-P. Raskin, "Could unsustainable electronics support sustainability?", *Sustainability*, vol. 13, no. 12, p. 6541, Jun. 2021.
DOI: 10.3390/su13126541

Unrelated journal papers

UJP1. F. Degavre, D. Bol, Z. Kieffer, R. Dekimpe, C. Desterbecq, T. Pirson, G. Sandu, S. Tubeuf, "Searching for Sustainability in Health Systems: Toward a Multidisciplinary Evaluation of Mobile Health Innovations", *Sustainability*, vol. 14, no. 9, p. 5286, Apr. 2022.
DOI: 10.3390/su14095286

Unrelated conference papers

UCP1. R. Dekimpe, M. Schramme, M. Lefebvre, A. Kneip, R. Saeidi, M. Xhonneux, L. Moreau, M. Gonzalez, T. Pirson, and D. Bol, "SleepRider: a 5.5 μW/MHz Cortex-M4 MCU in 28nm FD-SOI with ULP SRAM, Biomedical AFE and Fully-Integrated Power, Clock and Back-Bias Management", in *IEEE 2021 Symposium on VLSI Circuits*, Jun. 2021. pp. 1-2.
DOI: 10.23919/VLSICircuits52068.2021.9492365

UCP2. F. Degavre, D. Bol, Z. Kieffer, G. Sandu, C. Desterbecq, T. Pirson, R. Dekimpe, S. Tubeuf, "Accelerating sustainability transitions in care and health systems: How sustainable are e/m-Care and Health innovations?", in *Transforming Care Conference*, Jun. 2021.
DIAL:http://hdl.handle.net/2078.1/259092

List of acronyms

ALCA	Attributional LCA
BE	Back-End
BEOL	Back-End-Of-Line
CAGR	Compound Annual Growth Rate
CED	Cumulative Energy Demand
CLCA	Consequential LCA
CMOS	Complementary Metal-Oxide-Semiconductor
COP21	United Nations Climate Change Conference
CSR	Corporate Social Responsibility
DALI	Digital Addressable Lighting Interface
DC	Datacenter
DRAM	Dynamic Random Access Memory
EIO	Economic Input-Output
EMS	Electromagnetic Shield
ESH	Environment Safety and Health
ETSI	European Telecommunications Standards Institute
EU	Europe
EUV	Extreme Ultra-Violet
FE	Front-End
F-GHG	Fluorinated-GHG
GDP	Gross Domestic Product
GF	Global Foundries
GHG	Greenhouse Gas
GPU	Graphics Processing Unit
GSA	Global Sensitivity Analysis
GWP	Global Warming Potential
HEMS	Home Energy Management System
I4.4	Industry 4.0
IC	Integrated Circuits
ICT	Information and Communication Technologies
IDM	Integrated Device Manufacturer
...	...

...	...
IIoT	Industrial IoT
ILCD	International Life Cycle Data System
IoT	Internet of Things
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
IRDS	International Roadmap for Devices and Systems
IT	Information Technology
ITRS	International Technology Roadmap for Semiconductors
ITU	International Telecommunication Union
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LED	Light-Emitting Diode
LSA	Local Sensitivity Analysis
M2M	Machine to Machine
MCU	Microcontroller Unit
MTBF	Mean Time Between Failures
PA	Paris Agreement
PACE	Plan Air Climat Energie
PCB	Printed Cricuit Board
PED	Primary Energy Demand
PEF	Primary Energy Factor
PFC	Perfluorinated Compounds
PPAC	Power-Performance-Area-Cost
RAN	Radio Access Network
REC	Renewable Energy Certificates
RFID	Radio-frequency indentification
SMIC	Semiconductor Manufacturing International Corporation
STMicro	STMicroelectronics
TSMC	Taiwan Semiconductor Manufacturing Company
UMC	United Microelectronics Corporation
UNEP	United Nations Environment Programme
UPW	Ultra-Pure Water
WEEE	Wastes from Electrical and Electronic Equipment
WSN	Wireless Sensor Network

Acknowledgments

ENGAGING into a PhD thesis was not my initial goal when I started a one-year research position at UCLouvain in 2019, on the vast topic of *the socio-environmental impacts of ICT*. Nevertheless, it turned out to be a wonderful, multi-faceted, stimulating, and motivating journey towards the world of research and sustainability. Although it is clear that this journey requires a fair amount of efforts, perseverance and faith, it was also made possible thanks to the help of a devoted and thoughtful team. In this sense, I feel extremely thankful for the support I received over these four years.

First of all, sincere thanks to my supervisor David Bol, Jean-Pierre Raskin, and Jérôme Louveaux for steering me all along the way and for always lending me an attentive ear, bringing ideas to the table, challenging claims or methods, and encouraging me along this PhD journey. On a special note, I am deeply grateful to David Bol who had the creativity and courage to open an empty space for undone research on this topic. This was for me a fantastic opportunity to work on today's environmental challenges and a chance to think about the roles of engineers in our society. I would also like to thank my jury members, whose constructive comments and suggestions greatly improved this manuscript. In addition, thank the Fonds européen de développement régional (FEDER) and the Wallonia within the Wallonie-2020.EU Program for funding and supporting this research.

Of course, these four years would not have been so fun and instructive without all the UCLouvain colleagues. Thanks to the entire ECS group (Rémi, Louis, Pol, Martin, Marco, Adrian, Augustin, Sylvain, Maxime, Mathieu, Charlotte, Julien, Ludovic, Nicolas, Pengcheng, Roghayeh, Ludmilla, and Denis) for all the great time we spent together, let it be at the coffee machine, during meetings and projects, or during ECS social lunches and events. Thanks also for all the proofreading work which greatly contributed to improve the quality of my research papers. Moreover, I am grateful for the open-mindness and mutual caring between the researchers in the group. In particular, given that the ECS group engaged into a socio-environmental transition and hybridized its core expertise from pure integrated circuit design to ICT sustainability-related research topics.

In addition, my daily life at UCLouvain would certainly not have been so pleasant if it were not for the always cheerful technical and administrative staff of the electrical department: many thanks to Anne, Benoit, Souley, Brigitte, Isabelle, Pascal, Valeriya and Viviane for always kindly helping in various ways ranging from travel booking[1] to PCB soldering, and logistics support. Thanks also to Frédéric, Nadine, and Ronny who welcomed me and supported me in the chemistry laboratory for the chip desencapsulation.

I am also particularly grateful to my colleagues (some became friends!) with whom we started the doctoral summer school on Sustainable ICT (SICT)[2] in Louvain-la-Neuve: Thibault, Grégoire, Nicolas, Antoine, Georgiana, Pierre-Yves, Stéphanie, Delphine, Myriam, David, and Jean-Pierre. To this list adds people that joined in the organizing committee the years after and greatly contribute to the positive energy and forward-dynamic of the project: Noémie, Alex, Jan Tobias, Loïk, Sara, David, Louis, Lou, Lennart, Aina, Wiebe, Fieke, Iman, Blandine, and Maxime. I am really grateful to each of these people and to the participants for the very enriching discussions (and sometimes even collaborations) we had over the past four years. The SICT journey was really for me the first deep dive into inter- and transdisciplinary research and the opportunity to *experience* it, rather than read it. It gave me a glimpse of how I envision the future of research on sustainability and ICT topics.

Last but not least. My heartfelt thanks to all my friends, family members, and particularly my parents, brother, and Eléonore, for their unconditional support throughout this journey.

[1] Let us mention that we managed to avoid flying for all travels related to this thesis. For the record, this lead to a 40+ hours train and bus travel from Brussels to Plovdiv, Bulgaria for attending a conference.

[2] `https://www.sictdoctoralschool.com/`.

Introduction

Those who have the privilege to know have the duty to act,
and in that action are the seeds of new knowledge.
– Albert Einstein

OVER the last decades, the rapid development of Information and Communication Technologies (ICT) has deeply shaped our modern societies. More specifically, a sub-part of ICT called the Internet of Things (IoT) has gained significant momentum both in academia and industry. The IoT connects physical *things* to the Internet by embedding electronics in everyday objects, hence supporting ubiquitous computing. This has led to a steep growth of IoT devices over the last years, with market estimates projecting up to 200 billion connected objects in 2030 [1, 2, 3, 4, 5]. The goal is to incorporate electronic components into everyday appliances, transforming them into more sophisticated *smart* systems connected over the Internet and mobile networks [6]. Indeed, such connected devices require computing capabilities and connectivity features to transmit data acquired within their environment from the edge to a centralized management system, as illustrated in Fig. I.1. Examples of current IoT devices are smart watches and wearables, virtual reality headsets, connected home assistants, smart control valves, smart thermostats, smart video cameras, and smart lights, among others.

IoT is frequently presented as a way to make our lives more comfortable, and as an enabler to reduce the environmental footprint of our societies through their ability to monitor and optimize complex systems in real time. In fact, there is a considerable literature analyzing the benefits of the IoT and motivating the transition towards a more efficient use of resources and a better monitoring of the supply chains [7, 8, 9, 10, 11, 12]. In developed countries, the IoT therefore plays a key role in digitalization and is generally seen as an important building block to realize projects such as circular economy, or smart cities and buildings, agriculture, mobility and healthcare.

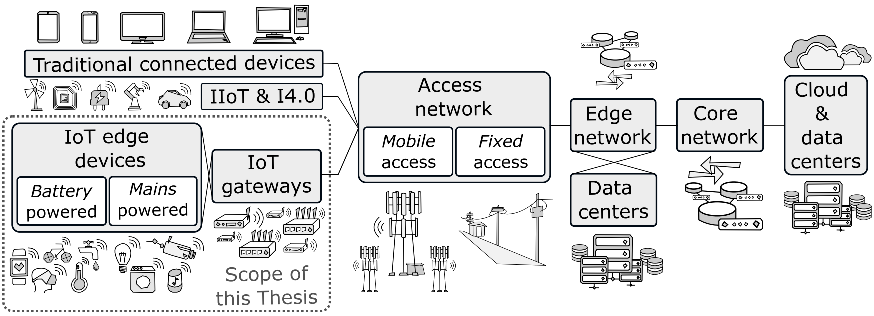

Fig. I.1 Illustration of the network architecture of IoT systems. This thesis focuses on the IoT devices.

However, the potential benefits of ICT (and IoT) come together with undeniable environmental burdens. In fact, ICT contribute to the increase of environmental impacts throughout the life cycle of its services and products [13]. They are referred to as direct environmental effects (as opposed to indirect or structural environmental effects) [14, 15] and occur during material extraction and refining, manufacturing, transport, use and disposal. To support the quantitative evaluation of environmental impacts, life cycle assessment (LCA) is generally used. It is a well-known and standardized methodology [16, 17] for evaluating the environmental impacts of a product (a good or a service) over several indicators, including global warming potential (GWP), water use, resource depletion, and toxicity for instance [16, 17]. Over the last decades, LCA has been applied extensively to the ICT sector, including ICT end-user devices (e.g, personal computers, laptops, smartphones [18, 19, 20]), telecommunication networks (e.g., routers and access network equipment [21, 22]), data centers (e.g., servers [23, 24]), and services like video streaming [25]. At a macroscopic scale, the absolute carbon footprint of the ICT was evaluated at about 1.2-2.2 $GtCO_2eq$ in 2020, or equivalently 2.1-3.9% of the world greenhouse gas (GHG) emissions [26]. Unfortunately, the carbon footprint of the IoT is not included in these estimates, and other environmental impacts are far from being taken into account. Given the facts that (i) IoT is the fastest-growing part of ICT [3] with a considerable number of end-devices to be deployed, and (ii) a significant part of the ICT footprint is already attributed to user devices (approximately between 30 and 50% depending on studies [26, 27]), the IoT must also be subject to systematic analyses regarding environmental impacts and sustainability [28, 29, 30]. Unfortunately, very little research has been conducted on this topic so far, leaving the environmental impacts of the IoT vastly under-explored [26]. Although few studies already address the environmental impacts of IoT devices, they are usually focused on specific devices and quantitative results over multiple indicators remain very scarce, or are focused on the use phase while leaving the other phases of the life cycle unconsidered [31, 32]. As of today, there is consequently a very limited understanding of the potential environmental effects of the IoT.

These concerns about the growing environmental impacts of IoT, and more specifically the carbon footprint of massively deploying IoT devices in the upcoming years, are very much anchored in the current environmental context of climate change. In fact, the actual socio-technical system is generally moving further away from a state of environmental sustainability [33, 34, 35], as six planetary boundaries[3] have already been exceeded due to the increasing pressure of anthropogenic activities on the environment [34, 38, 39]. This goes to the extent that, according to geologists and environmental chemists, it marks the beginning of a new geological epoch called the *Anthropocene* [40, 41]. The current global warming situation leading to climate change and the strong loss of biodiversity call all economic sectors and human activities to quickly decrease their GHG emissions [42, 43], which also applies to ICT (and consequently IoT). This hence raises questions on the role(s) and on the environmental effects of digital technologies, especially given the current policies generally pushing towards more digitalization[4] and the important financial investments in sectors developing digital technologies [44]. Indeed, the development of digital technologies is moving forward at a frantic rate since a few decades, further supported by other drivers such as the improvements of the quality of life and the expectancy that these technologies will put our developed societies on tracks towards less resource intensive patterns. The last IPCC report [35] explicitly mentions the ambivalence of the environmental effects of these technologies, being at the same time potential enablers for GHG mitigation and a threat for environmental sustainability. This further highlights the need to thoroughly understand the environmental impacts associated with the IoT (going well beyond its carbon footprint evaluation) to avoid worsening the current environmental situation.

This thesis therefore aims at improving the current knowledge regarding the environmental impacts associated with the materiality of IoT. This work is primarily dedicated to provide scientific quantification of environmental impacts for the IoT. Throughout this thesis, a particular attention is given to the *embodied*[5] environmental impacts given the current lack of considerations on this matter in the field of the IoT. In the remainder of this introduction, we present the research goals and the approach that is undertaken throughout this work, followed by a description of our contributions and the outline of this thesis.

[3]The framework of planetary boundaries identifies and quantifies nine planetary boundaries that must not be transgressed in order to maintain the Earth in a "safe operating space for humanity", similar to its state for the last ten to twelve thousand years [36, 37].

[4]For instance, in the European Green Deal.

[5]The environmental impacts associated with life-cycle stages other than the use phase, and more specifically life-cycle stages contributing to the production of a product.

1.1 Research approach and goals

In this research, we chose to adopt a quantitative approach from engineering sciences to foster the systematic evaluation of the environmental impacts of IoT devices through LCA. Nonetheless, such a bottom-up approach would mainly be focused on the technology itself, without relating to the bigger picture of environmental sustainability and the top-down constraints calling for a *global* reduction of the impacts of anthropogenic activities on the environment [35, 43]. The research question at the core of this thesis hence combines these two aspects, and can be summarized as follows:

To which extent could the systematic LCA of IoT devices help keeping the IoT footprint within environmental limits?

This question first requires to understand *why* systematic LCA is needed for IoT devices, and *how* to implement it, which is the focus of the first part of this thesis.

1.1.1 Systematic LCA for the IoT

As previously pointed out in this introduction, current estimates for the carbon footprint of ICT do not account for the impacts of the IoT, albeit it is one of the main driver for the current and upcoming increase of ICT end devices [26]. Better understanding the additional footprint introduced by the emergence of IoT is hence crucial. However, it is substantially complicated by the high heterogeneity in IoT devices and applications. In fact, unlike already existing devices in the ICT [18, 19], IoT devices can strongly vary in composition depending on the applications they target and on how they have been designed. We could carry out a specific LCA for a wide variety of IoT devices, but this would require a lot of time and the access to a large number of physical IoT devices. This, together with the important lack of LCA results for IoT devices in the current literature, prevent such an approach. In **Chapter 2**, we hence investigate **how to streamline the carbon footprint evaluation for the production of a wide variety of IoT devices, while taking into account the inherent heterogeneity between them**. We propose the concept of *hardware profiles* for qualifying IoT devices, and build a consistent framework to streamline the carbon footprint evaluation of IoT devices under similar boundaries and modeling assumptions. We use this framework on four case studies and benchmark our results with the few studies available, mainly from Apple and Google.

As observed traditionally for end-users electronic devices, our framework points out that integrated circuits (ICs) can be responsible for a significant part of production impacts of IoT devices [19, 20]. Unfortunately, the environmental footprint from IC production typically suffers from a high variability between existing evaluations. In fact, even if data exist to quantify the environmental impacts of ICs, there is no general unified understanding on the topic. This is very problematic as ICs are one of the key building blocks of electronic systems, and thus inevitable components for LCA of ICT products [18, 19]. In **Chapter 3**, we **explore the main sources of variation in the available studies providing data on the environmental footprint of IC production**. We conduct an extensive literature review on the topic and identified twenty-seven studies from four different literature categories, i.e., foundry reports, industrial roadmaps, scientific literature, and state-of-the-art commercial LCA databases. In order to go beyond the sole evaluation of the carbon footprint, we considered also two other environmental indicators, namely energy consumption and water consumption.

We argued in Chapter 2 that using our streamlined approach based on hardware profiles is an interesting way to foster the systematic evaluation of environmental impacts of IoT devices. Yet, our framework only focuses on the carbon footprint evaluation of IoT device production, leaving aside the other phases of the life cycle and other environmental indicators. Moreover, it would be worth comparing the results of the streamlined approach with the results that would have been obtained with a full LCA. In **Chapter 4**, we therefore examine **to which extent the gaps between streamlined and full LCA approach could affect the systematic LCA of IoT devices**. We illustrate this with a concrete case study and we carry out a full-scope multi-indicator LCA for a real-life deployed IoT solution of smart public lighting. This chapter concludes the first part of the thesis, which shows *why* systematic LCA is needed for IoT devices, and *how* to foster it in practice.

I.1.2 Environmental perspectives and limits for the IoT

Based on the work carried out in the first part of this thesis, a predictable (and conventional) approach would be to carry out eco-design in order to propose alternative version(s) of these IoT solutions with better environmental performance [45, 46, 47]. However, we rather dedicate the second part of this thesis at **understanding the limits of systematic LCAs for IoT with respect to the bigger picture of environmental sustainability**. We provide environmental perspectives for the IoT in the Anthropocene by integrating explicitly environmental limits such as planetary boundaries or Paris Agreement targets.

Consequently, **Chapter 5** aims at **unveiling the limits of LCA to assess environmental sustainability**. It starts by providing historical insights regarding the development of LCA in the 1960's to root perspectives in a socio-technological context. Then, we build upon existing scientific literature [33, 48, 49, 50] and further explore the environmental pitfalls when focusing solely on improving relative environmental efficiency metrics. Indeed, LCA is an effective tool to identify the environmental hotspots and reduce the environmental footprint of a product[6], but it hardly relates to global environmental limits. We investigate this question in the specific field of electronics and IoT notably by putting the results of the full LCA conducted in Chapter 4 in perspective with planetary boundaries. In addition, we carry out an historical macro-analysis to learn from the historical evolution of the relative environmental impacts associated with the production of ICs. We use data from the period 1980-2010 and the results of the analysis conducted in Chapter 3 for the period 2010-2020 to put these relative environmental improvements in perspectives with the changes required to reach 1.5°C Paris Agreement target, if we also account for the constant increase in ICs production volumes.

In **Chapter** 6, we shift from a product-oriented approach to a more holistic approach in order to **understand how the consideration of top-down global environmental limits can impact the ongoing IoT massive deployment of IoT devices**. We start by investigating to which extent the carbon footprint of producing IoT devices for a worldwide massive deployment could be a threat for ICT environmental sustainability. We conduct a forecasting study to evaluate the carbon footprint generated by the production of a wide variety of IoT devices for a worldwide massive deployment from 2018 to 2028. Then, the last part of this chapter aims at identifying an approach to support the evaluation of the environmental relevance of IoT solutions with respect to environmental limits, while integrating direct, indirect, and structural environmental effects on the long-term. We hence explore different types of future studies with a set of required features and illustrate the potential of *backcasting* studies with the conceptual use case of smart public lighting in Belgium over the period 2020-2050.

I.2 Contributions and outline of the thesis

Several original and significant contributions to state-of-the-art knowledge are proposed in this thesis, which is organized in two different but complementary parts. The first part focuses on the systematic LCA for the IoT in Chapters 2, 3, and 4 while the second part builds upon the work carried out in the first part and provides environmental perspectives by considering environmental limits in Chapters 5 and 6. Main contributions are summarized below, together with an outline of the thesis.

Chapter 1 introduces key concepts and background knowledge regarding environmental limits and LCA methodology to provide readers that are new to the field with the basics necessary to understand the work done in this thesis. This

[6] According to its functional unit, as defined in the LCA jargon [16].

chapter can hence be skipped by expert readers as a specific state-of-the-art section is provided at the beginning of each chapter, when relevant.

In **Chapter** 2, we introduce the concept of *hardware profiles* to foster the systematic environmental assessment of IoT devices. We propose a framework providing quantitative results to streamline the evaluation of the production carbon footprint of many IoT devices under similar boundaries. We then benchmark this framework on four case studies of consumer IoT devices. In addition, we evaluate the variability existing between the carbon footprint of a variety of IoT devices, hence demonstrating that the heterogeneity inherent to IoT devices must be considered. The content of this chapter is adapted from [JP1], and supplementary material is provided in Appendix A and Appendix B.

In **Chapter** 3, we carry out the first extensive literature review of currently available LCA studies on the environmental impacts of IC production. We then use this review to conduct both qualitative and quantitative analyses. To support the qualitative analysis and compare the scopes of the studies, we define ten objective features specific to IC production that could serve as a basis for further standardization in this field. By classifying each source with respect to these features, we provide the first systematic identification of scope mismatch between existing studies and partially explain causes of variation. In addition, the quantitative analysis highlight the environmental impacts of technology downscaling and provide estimates for foundries based on publicly available environmental reports. It is to date the only published quantitative review on the environmental impacts of ICs gathering four different literature categories. Furthermore, by providing an online supplementary material with all data and all assumptions used in the review, we aim at fostering transparency and stimulating the scientific community to further contribute to this research field. The content of this chapter is adapted from [CP2] and [JP2], and supplementary material is provided in Appendix C.

Chapter 4 concludes the first part of this thesis with a detailed full-scope and multi-indicators LCA of a real-life IoT solution for smart public lighting. To the best of our knowledge, this is to date the most comprehensive LCA study for a real-life deployed IoT solution. Let us mention that we also include an updated review of energy intensity factors to transfer data on the ICT infrastructure. By comparing the results of our streamlined approach based on hardware profiles and the results of the full LCA, we illustrate the trade-offs between both approaches. We show that although a streamlined approach is more convenient as it quickly provides quantitative results while being accessible to users with a limited initial expertise, it should not replace full LCA for IoT in the long-term but rather complement it. The content of this chapter is adapted from [CP1], and supplementary material is provided in Appendix B and Appendix D.

In **Chapter 5**, we provide the first historical macro-analysis on the environmental footprint of IC production. This unveiled the limits of further improving the environmental indicators per cm^2 and thus, the limit of CMOS technology downscaling in being an effective solution for environmental sustainability, if not combined with sobriety. In fact, this historical macro-analysis reveals the existence of a rebound effect at the hardware level and illustrate why relative environmental metrics are not sufficient to foster environmental sustainability. By providing a simple conceptual model of the link between absolute and relative environmental impacts, we also point out the insidious effects of increasing the production volumes on environmental efficiency metrics. The content of this chapter is adapted from [CP1], [CP2], and [JP2]. Supplementary material for the historical macro-analysis is provided in Appendix C

Finally, in **Chapter 6** we further conduct macroscopic analysis to show the implications of including global environmental limits in the context of the IoT massive deployment. Our forecasting study reveals conflicting trends between the carbon footprint generated by the worldwide production of IoT devices and the GHG reduction that would be required if the ICT's carbon footprint was to follow a pathway in line with the 1.5°C Paris Agreement target. Then, we highlight limitations of forecasting studies and identify *backcasting* as a promising approach taken from the field of future studies. We illustrate its potential to integrate the multi-faceted environmental effects of IoT and identify IoT solutions that should be fostered, or conversely, the ones that should be discouraged (re-designed or even simply abandoned) for ecological reasons. This should be understood as a concrete suggestion of a strategy to help keeping the IoT within environmental limits, therefore going beyond the mere application of systematic LCA for IoT. The content of this chapter is adapted from [CP1] and [JP1], and supplementary material is provided in Appendix E.

1

Basics

If you want to go fast, go alone, if you want to go far, go together.
– African Proverb

THIS chapter aims at providing the basics regarding environmental limits in the Anthropocene, ICT methodological fundamentals terminology, and most importantly minimal knowledge regarding the LCA methodology.

1.1 Environmental sustainability and limits

This section starts by clarifying the concept of (environmental) sustainability and Anthropocene. Then, it describes two important science-based environmental limits used in this thesis, i.e., planetary boundaries and Paris Agreement targets.

1.1.1 Sustainability

Sustainability is a wide, complex, and multi-faceted topic which makes its definition particularly difficult. In fact, there is no unique definition of sustainability making consensus. One of the most well-known definition of sustainable development was coined by the United Nations' Brundtland Commission on Environment and Development in 1987 [48, 51]. In their report called *Our Common Future*, they define sustainable development as a "... development that meets the needs of the present without compromising the ability of future generations to meet their own needs". Nevertheless, even if this definition highlights the important concepts such as human needs and responsibility for future generations, it remains very unclear what are (and what will be) the needs of each generation. Moreover, it defines sustainable development but not the concept of sustainability in itself, which can be used with different connotations in the literature [51]. In reaction to this well-known report, many different definitions have been proposed. While they all embed different nuances, Hauschild et al. [51] proposes a compromise definition of sustainability based on four dimensions: (i) the measure of welfare understood as the *need*, *happiness*, *utility*, or *aspiration*, (ii) the inter-generational equity to consider the distribution of welfare globally and locally among different generations, (iii) the intra-generational equity to consider the distribution of welfare within a given generation, and (iv) the inter-species equity, as most sustainability definitions are anthropocentric.

However, Hauschild et al. further points out that "there is no explicit consideration of environmental conservation in most definitions of sustainability" [51]. In this thesis, we understand *environmental sustainability* as a subpart of sustainability which only accounts for the environmental aspects. We acknowledge that it is a reductionist view of sustainability, as it does not consider social and economic aspects. Yet, in this thesis we assume that environmental sustainability is a necessary condition for others sustainability aspects, as they could (most probably) not be sustained without the service provided by the environment and/or its ecosystems at some point. Considering a long-time perspective (inter-generational equity) and accounting not only for humankind (inter-species equity) further supports this assumption. Nevertheless, the question whether the other aspects of sustainability could be ensured without environmental sustainability cannot be tackled from the sole perspective of engineering sciences and a clear-cut answer to this question is clearly outside of the scope of this thesis. Moreover, even if our assumption regarding the central place of environmental sustainability was proven to be wrong, it would not cause irreparable prejudice to the environment, contrarily to ignoring this aspect. We therefore consider this approach to be precautionary. The rest of this section aims at providing more inputs for this definition, including the notions of environmental limits and planetary boundaries to define a *safe operating zone* for the humanity. In fact, environmental limits are intrinsically related to the definition of environmental sustainability if we consider the Earth system in a long-term perspective.

1.1.2 The Anthropocene

The Earth system undeniably went through many significant environmental changes during its history. Yet, for the past ten to twelve thousand years, the post-glacial geological epoch (called the Holocene) was characterized by a very unusual stability in terms of temperature and climatic conditions [41, 48]. These favorable conditions have been the cradle of humankind, as we know it today. However, this stability is now seriously threaten by the rapidly growing impacts of human actions on their surroundings. In fact, the pressure of anthropogenic activities has become the main driver of global environmental change (including impacts on Earth's ecosystems), to the extent that humankind is now considered as a major geological force [41, 52]. According to geologists and environmental chemists, this marks the end of the Holocene and the beginning of a new geological epoch, called the Anthropocene[1] [37, 52]. The name is a combination of anthropo- from the Ancient Greek (*anthropos*) and -cene (*kainos*), meaning *human* and *new* or *recent*, which emphasizes the central role of humankind in geology and ecology [41].

The start date of the Anthropocene is controversial in the literature [36, 40]. Initially, Paul Crutzen [36, 52] pointed out the industrialization as a starting point near the end of the 18^{th}century, then supported by the Industrial Revolution which started in England during the 19^{th}century [41]. Yet, Steffen et al. [40] carried out a trend analysis in the 2000's and concluded that the Anthropocene started in the 1950's. In fact, they revealed the sudden acceleration of the *human entreprise* in the second part of the 20^{th}century, often referred to as the *Great Acceleration*. Although the Great Acceleration has supported major improvements in several sectors, it has been accompanied by a rapid increasing pressure of humankind on the Earth system [40], as shown in Fig. 1.1 and Fig. 1.2. The necessity to identify the drivers behind this overall increasing of environmental impacts has led to the use of the well-known IPAT equation[2], expressed as

$$I = P \cdot A \cdot T \tag{1.1}$$

where I is the environmental impact, P is the population size, A is the affluence (i.e., the consumption of products and services per capita), and T the technology factor which captures the environmental intensity of a technology (being a product, a good, a material, or a service). The general conclusion that can be drawn from Fig. 1.1 and Fig. 1.2 is that I increased for all environmental indicators whereas T generally improved (or stagnated) through time due to technology efficiency improvements witnessed since the 1950's. The combined effect of $(P \cdot A)$ is therefore

[1] The term was first introduced by Paul Crotzen in 2000 [36]. Nonetheless, it has not yet been officially recognized as a subdivision of geologic time and it is mostly informally used in scientific context. The Anthropocene remains hence a *proposed* new epoch in Earth history [36].

[2] The factors are considered to be independent at the first order.

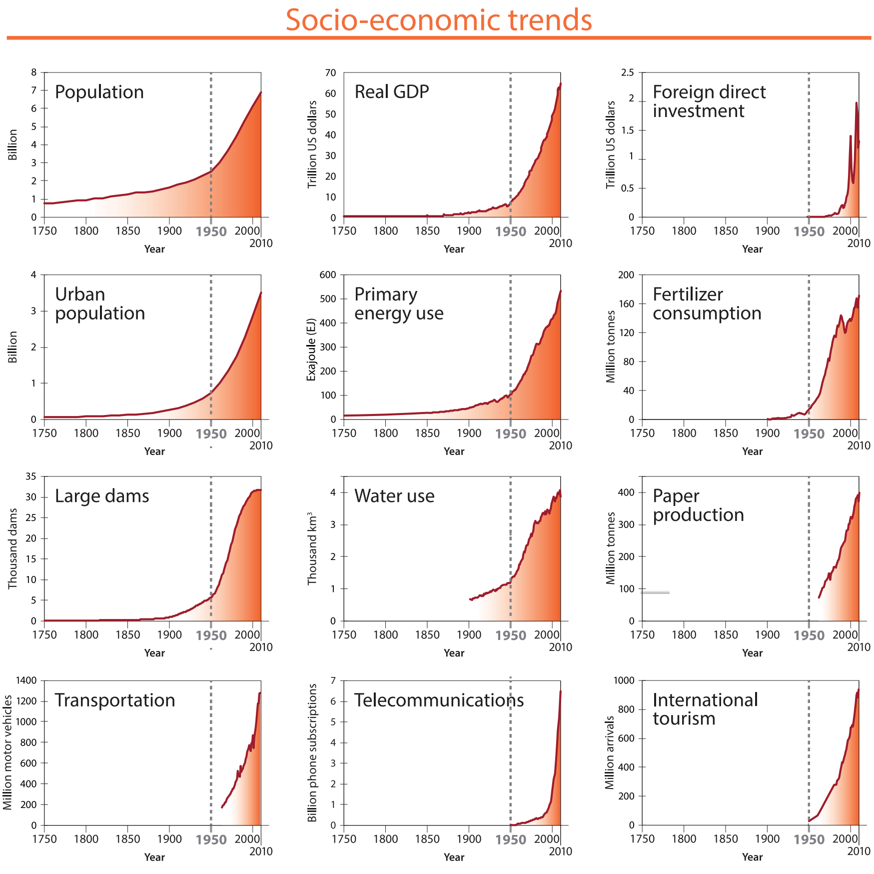

Fig. 1.1 Illustration of the Great Acceleration through trends from 1750 to 2010 in globally aggregated indicators for socio-economic development. Figure adapted from [40]. All details can be found in the original publication [40].

pointed out as the main driver for the increase of environmental indicators [51]. Yet, it is important to notice that if the world population (P) as almost been multiplied by 3 over the period 1750–2010, the increase of other socio-economic indicators have increased even faster, hence showing that the affluence also increased.

It is important to stress out that human history had never witnessed such a rapid and extensive change on the world's ecosystems before. The Anthropocene is also characterized by the massive use of fossil fuels which significantly increased

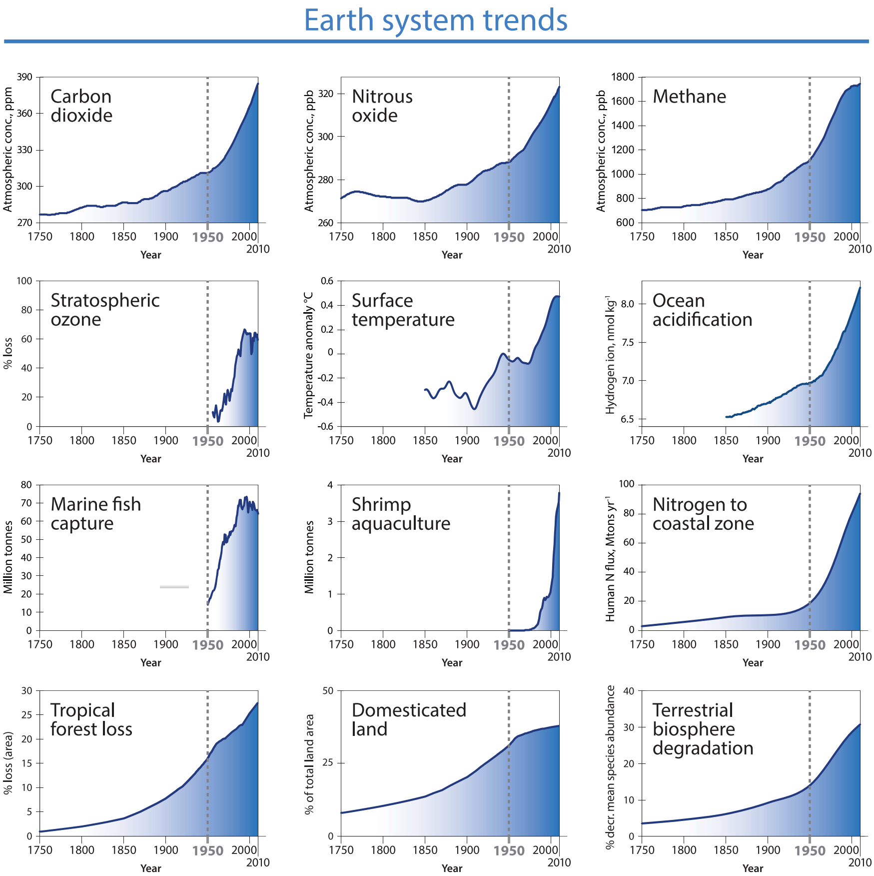

Fig. 1.2 Illustration of the Great Acceleration through trends from 1750 to 2010 in indicators for the structure and functioning of the Earth system. Figure adapted from [40]. All details can be found in the original publication [40].

the concentration of greenhouse gases (GHG) in the atmosphere from about 280 ppm in the pre-industrial level [36] up to more than 350 ppm in the 2000's [41], and still rising [53]. This also led to the sixth global mass extinction of species where both terrestrial and marine ecosystems are impacted with unprecedented rates of species loss [41]. The staggering growth of all these environmental indicators in the Anthropocene raises concerns regarding the capacity of the Earth system to withstand such environmental pressure, which is discussed in the next section.

1.1.3 Planetary boundaries

The framework of planetary boundaries was first introduced in 2009 by twenty-nine leading Earth-system scientists from the Stockholm Resilience Centre [37], with the main objective of preventing human activities from causing environmental changes that could in turn jeopardize the self-regulation of natural systems ensuring stable conditions for humankind. To help reaching this goal, they identified and quantified planetary boundaries that must not be transgressed in order to maintain the Earth in a Holocene-like state [36]. For this reason, planetary boundaries are often defined as a "safe operating space for humanity with respect to the Earth system" [37]. The concept of *safe operating space* is further echoed by Kate Raworth [54, 55] who extended the planetary boundaries framework to integrate social dimensions by adding a social foundation based on standards for human wellbeing established by the sustainable development goals (SDG) [56]. Indeed, as the planetary boundaries framework from Rockström and colleagues only focuses on environmental considerations, it does not capture inequalities regarding where resources are being used and by whom [54]. Let us mention that Rockström and colleagues very recently extended their framework to integrate similar considerations [57]. Nevertheless, as this work only focuses on environmental considerations, we consider the original planetary boundaries framework.

The planetary boundaries framework is based on the observation that many subsystems of the Earth react in a nonlinear and complex way to changing pressures. More specifically, abrupt responses can be observed if threshold levels are crossed for certain key variables, revealing the sensitivity of these subsystems. These abrupt changes can lead to detrimental or even catastrophic consequences for humans, hence the need to remain in a safe operating space. A key feature of this framework is that the authors define science-based *absolute* boundaries for man-made impact on the environment [37, 48], which holds for current and future generations. The framework defines nine planetary boundaries[3], as illustrated in Fig. 1.3(a): climate change; change in biosphere integrity (functional and genetic diversity); biochemical flows (nitrogen and phosphorus cycles); stratospheric ozone depletion; ocean acidification; freshwater use; land-system change; introduction of novel entities; and atmospheric aerosol loading. The planetary boundary is usually placed below the estimated threshold as illustrated in Fig. 1.3, mainly to account for the uncertainty of its precise position but also to consider the society time response to react to early warning signs [34]. There is no doubt that the presence of feedback loops and inherent uncertainty in natural systems significantly complicates the estimation of these planetary boundaries and their associated thresholds [36]. Yet,

[3] The original planetary boundaries framework has been revised and updated in 2015 [34], including the consideration of regional-level heterogeneity and updates on the quantification of most planetary boundaries. Yet, the core idea remains unchanged.

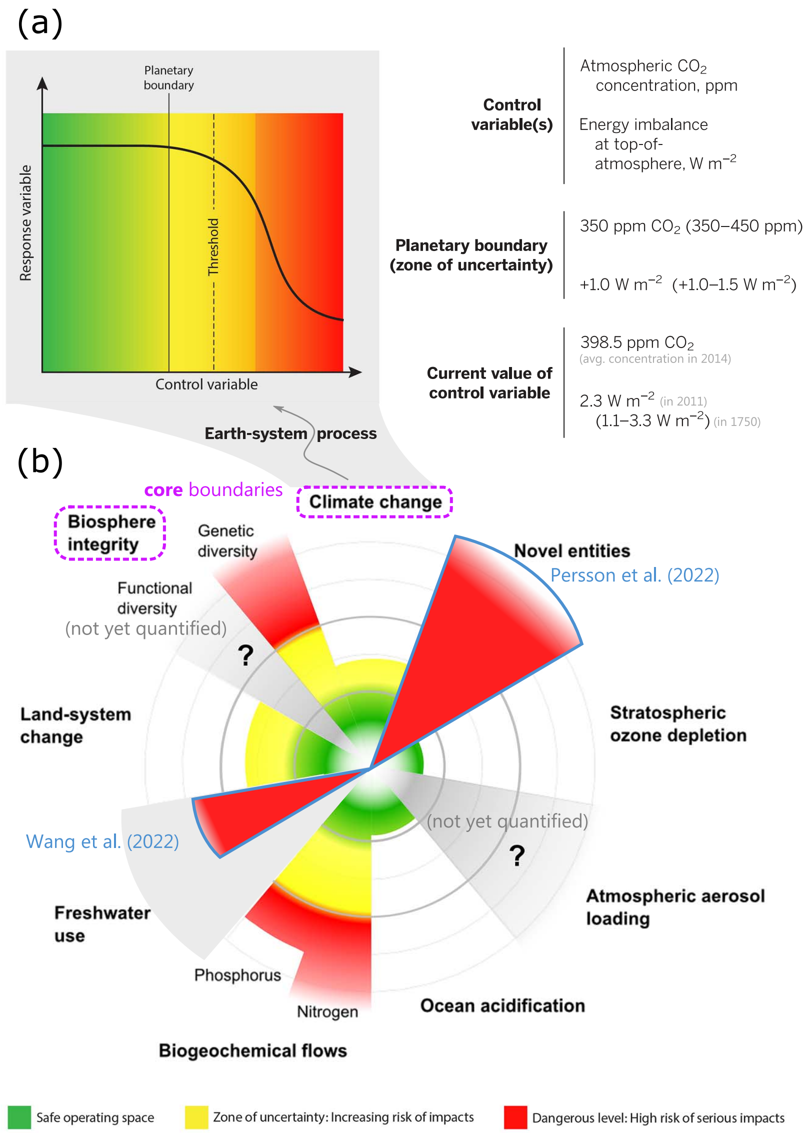

Fig. 1.3 (a) Conceptual illustration of control variable and planetary boundary in the case of climate change. (b) Illustration of the current status of the control variables for seven of the nine planetary boundaries. Figure adapted from [34].

even if the exact implications are not thoroughly understood as it depends on the current knowledge of environmental sciences, Steffen et al. argue that according to the precautionary principle, it would be unwise to drive the Earth system substantially away from its stable Holocene-like conditions [34].

According to [34, 36], four planetary boundaries were already exceeded in 2015, i.e., climate change, biosphere integrity, biochemical flows, and land-system change. Moreover, recent publications from Persson et al. [39] and Wang et al. [38] addressed two more planetary boundaries that were not quantified in 2015 [34], i.e., respectively the novel entities and freshwater use[4]. These studies showed that both are also exceeded (and in particular novel entities), raising the total number of exceeded planetary boundaries to six, or equivalently two third of the planetary boundaries. Moreover, in a recent interview from Will Steffen [36], the author of the framework explicitly stresses out that "[...] In general, most of the control variables for the boundaries are moving away from the safe operating space, or, if they were within, are moving closer to the boundary itself [...], in the wrong direction".

Albeit the planetary boundaries are defined individually with their associated quantities and processes, they are far from being independent from each others and even deeply interlinked. Focusing on one boundary at the detriment of the others has hence a limited interest, as transgressing the others will undoubtedly put the system under serious risk. For instance, Rockström et al. explains that "the climate-change boundary depends on staying on the safe side of the freshwater, land, aerosol, nitrogen–phosphorus, ocean and stratospheric boundaries" [37]. These interactions between multiple interacting processes highlight the important complexity inherent to global environmental sustainability [34]. Nevertheless, based on an analysis between the interactions between all boundaries and their overall fundamental importance for the Earth system stability, the authors of the framework proposed a two-level hierarchy of boundaries. Two out of the nine planetary boundaries (i.e., climate change and biosphere integrity) are recognized as *core* boundaries, meaning that they can change the state of the Earth system on their own [34, 36]. Unfortunately, both are already exceeded, especially in the case of biosphere integrity with the upcoming extinction of around one million animal and plant species within decades [36, 43]. The alarming conclusion that the current rate of biodiversity loss cannot be sustained without a significant erosion of ecosystem resilience is clearly echoed in the last report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) [43]. Regarding climate change, the issue is now well understood and well documented by the IPCC [35], especially the relationship between the rising concentrations of

[4]Wang et al. focuses only on green water, i.e., water from terrestrial precipitation, evaporation and soil moisture [38].

GHG emissions in the atmosphere and the warming of the climate system[5] [40]. Since 1990, the IPCC has been calling for rapid and strong reductions of GHG emissions, while they are still on the rise today. This reveals the important gaps between science-based knowledge and their global uptake in policy making at global, national, and regional scales. In the next section, we further develop the climate change issue with the Paris Agreement.

1.1.4 Paris Agreement and decarbonization pathways

The Paris Agreement (PA) is a legally binding international treaty on climate change which was adopted in 2015 by 196 parties during the UN Climate Change Conference (COP21) in Paris, France [60]. The main objective of the Paris Agreement is to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels" and pursue efforts "to limit the temperature increase to 1.5°C above pre-industrial levels" [60]. This aims at limiting the effects of climate change, including frequent and severe droughts, heatwaves and rainfalls. However, the Paris Agreement does not specify *how* to reach these goals, nor how fast GHG and CO_2 emissions need to be reduced [61].

Even if the Paris Agreement's goals are aligned with science-based targets, considerable gaps also remain with national commitments [62]. In 2017, Rockström and colleagues attempted to address that problem by proposing a concrete roadmap for rapid decarbonization to make Paris goals a reality [62]. They framed the Paris Agreement targets in terms of a global roadmap aiming at halving CO_2 emissions every decade from 2020 to 2050. Concretely, this means that global CO_2 emissions reach a peak no later than 2020 and gross emissions decline from about 40 $GtCO_2$/year in 2020 down to $\sim$5 $GtCO_2$/year by 2050. Rockström and colleagues argued that the proposed decarbonization roadmap, called *Carbon Law*, could be applied "to all sectors and countries at all scales" [62]. Similarly, the United Nations Environment Programme (UNEP) issued the *Emission Gap* report in 2019, where they also proposed global decarbonization pathways consistent with Paris Agreement targets [63]. More specifically, they proposed two pathways to meet the 2°C and the the 1.5°C targets. This yields respectively a reduction of CO_2emissions by 2.7%/year and 7.6%/year on average, if reductions effectively start in 2020.

The comparison of these two global decarbonization roadmaps consistent with the Paris Agreement is shown in Fig. 1.4, and put in perspective with the remaining cumulative carbon budget disclosed in the AR6 IPCC report [53]. The global challenge is clear: we need to drastically reduce the global CO_2 emissions *within*

[5]Global warming potential is caused by GHG emissions which are quantified as $kgCO_2$-equivalent ($kgCO_2eq$). They represents the concentration of carbon dioxide that would cause the same radiative forcing as a given mixture of CO_2 and other forcing components [58, 59].

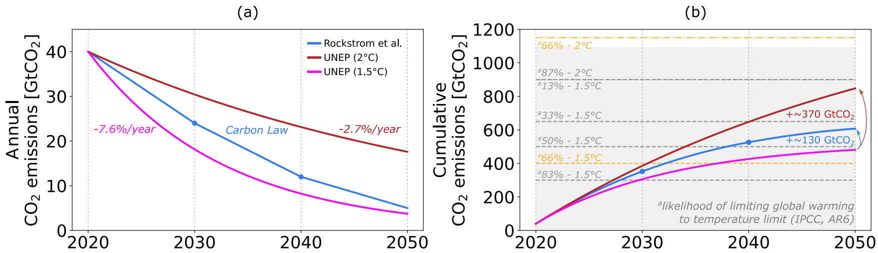

Fig. 1.4 Comparison of the decarbonization roadmaps from Rockström et al. [62] and UNEP [63] for (a) annual CO_2 emissions, and (b) cumulative CO_2 emissions. The likelihood of limiting global warming to the temperature limits shown in (b) are taken from the IPCC AR6 report [53]. Remaining carbon budget estimates consider the warming from non-CO_2 drivers, as implied by the scenarios assessed in SR1.5 [53].

the next decades. Yet, Fig. 1.4 also illustrates that although two pathways reach (almost) the same target for annual emissions, their cumulative emissions can differ as it is the integration of annual emissions over time. This stresses out the urgency of starting serious climate action, as delays today will require even greater cuts in the future to remain within a fixed carbon budget by 2050.

Although these carbon roadmaps propose a link between the top-down global targets from the Paris Agreement and concrete pathways, they do not take into account inequalities for GHG reductions, local constraints, policy reluctance, or system inertia, which would further complicate the allocation of GHG reductions in practice. Nonetheless, these roadmaps already offers a first pragmatic strategy[6] for framing carbon-related environmental limits in a quantitative way.

[6]Other similar strategies or initiatives also exist for companies, such as the Science-Based Targets initiative (SBTi) [64].

1.2 Direct and indirect environmental effects of ICT and IoT

This section starts by providing definition for the terms *ICT* and *IoT*, as they are extensively used throughout this thesis. Then, it introduces the taxonomy used in the literature to structure the environmental effects of ICT, and illustrate it on the case of IoT.

1.2.1 ICT and IoT definitions

Although there are various uses of the term **ICT** nowadays, it is generally used to denote all devices, goods, services, software, applications, and technologies used to compute, share information and communicate in the digital world. It is also used to denote the activity sector involved into high technologies dealing with information and communication applications. The classification issued by the Organisation for Economic Co-operation and Development (OECD) is often used as an official definition of the ICT sector, which is detailed in the fourth revision of the International Standard Industrial Classification of All Economic Activities (ISIC) published in 2008 [65]. This definition is first intended to provide a common international basis to measure the part of the economic activity generated by the production of ICT goods and services, which must be "[...] primarily intended to fulfill or enable the function of information processing and communication by electronic means, including transmission and display" [65]. If the development of the telegraph and the telephone during the 1900's could be seen as the roots of ICT, the emergence of the radio, the television, and the Internet has extended the concept. Over the last decades, the fast development of digital devices and services in almost every activity sectors further participates to the ever increasing list of goods and services that falls into the evolving concept of ICT. This is the case for connected devices and applications supporting the IoT, for instance.

Providing a clear and unique definition of what falls into the concept of **IoT** is also challenging, as there are manifold definitions existing in both grey and scientific literature [66, 67]. Although the exact definition of IoT is still in a forming process as it is an emerging paradigm, a general description can be sketched through a combination of existing definitions. For instance, the ITU Y.2060 technical recommendation defines the IoT as "a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies", where a *thing* is "an object of the physical world or the information world[7], which

[7]Examples of physical things: surrounding environment, industrial robots, goods and electrical equipment. Examples of virtual things: multimedia content and application soft-

is capable of being identified and integrated into communication networks" [68]. Another definition from IoT Analytics is "a network of internet-enabled physical objects [...] that typically interact via embedded systems, some form of network communications, as well as a combination of edge and cloud computing" [69]. A third generic definition provided by Li et al. [67] depicts IoT as "a dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols; physical and virtual *things* in an IoT have identities and attributes and are capable of using intelligent interfaces and being integrated as an information network". Through these definitions, it becomes clear that the IoT adds one more dimension (*any thing* communication) to the ICT which already provide *any time* and *any place* communication [68]. Fundamental characteristics of the IoT are therefore the huge number of heterogeneous and dynamic objects envisioned to be (inter-)connected to the Internet through a multi-layer[8] architecture [67, 68, 70]. The IoT hence relies on a "disruptive level of innovation in today ICT world" [70] and plays a key role in digitalization, as it supports a wide variety of projects such as circular economy, or smart cities and buildings, agriculture, mobility and healthcare [12].

In practice, the choice of what devices should be labeled as IoT devices may seem relatively arbitrary [71]. This adds to the apparent fuzziness around the concept of IoT, as it is expected to integrate several leading technologies, such as wireless sensor networks (WSNs), intelligent sensing and actuation, data mining from the physical world, machine-to-machine (M2M) communication, edge decision-making, cloud computing, and security protection [68, 67] both for consumer and enterprise applications[9]. For instance, the inclusion of radio-frequency identification (RFID) technology or QR-codes in the scope of IoT really depends from one definition to another [69, 70, 71], whereas traditional connected devices such as connected personal computers, tablets, or smartphones are usually not considered as IoT devices, even though these may be part of the overall solution setup. A high-level classification of different connected devices was proposed in a 2019 IEA's report [31], where groups and categories are defined to structure several examples of connected devices (including but not limited to IoT), such as smart meters, smart lights, smart sensors for automation in building, smart healthcare devices, and IoT gateways. Similarly, a classification of the applications requiring IoT devices is provided in [70] with the four main domains being (i) transportation and logistics, (ii) healthcare, (iii) smart environment (home, office, plant), and (iv) personal and social.

ware.

[8]The IoT architecture is often divided in four main layers, i.e., device layer, network layer, service layer, and application layer [68, 67].

[9]For enterprise and industrial applications, the term Industrial IoT (IIoT) is often used.

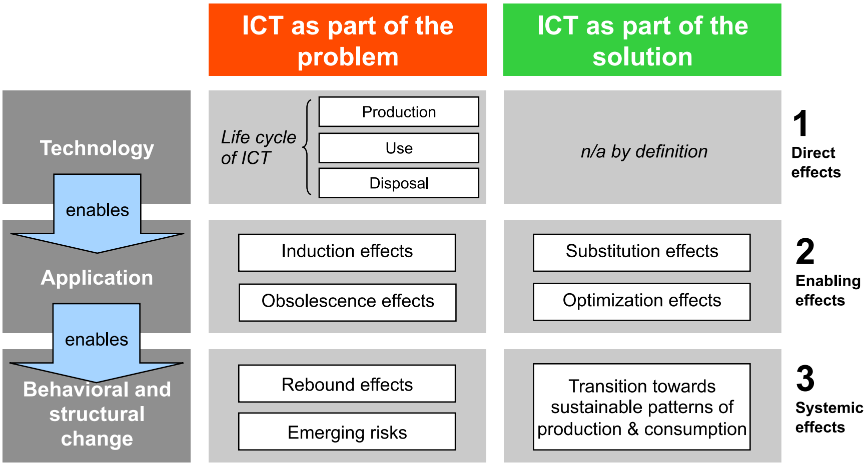

Fig. 1.5 A matrix of ICT environmental effects. Figure from Hilty and Aebischer [14, 75]. The definition of each term can be found in the original publication [73].

1.2.2 The three-level taxonomy of the environmental effects

As pointed out by the ITU [72], ICT distinguishes itself by its *double-edged nature* as it is at the same time the cause of detrimental environmental impacts at each stage of its life cycle, and the enabler of efficiency improvements in a wide variety of sectors and applications through the digital solutions it provides. The environmental sustainability framework introduced by Berkhout and Hertin [15] (and popularized by Hilty et al. [73] with the matrix shown in Fig. 1.5) offers a simplified view of ICT as being at the same time "part of the solution" and "part of the problem". Albeit this classification is conceptually appealing as it tends to classify what fosters environmental sustainability and what does not, it embeds inherent shortcomings especially by considering that the different effects are independent. The authors themselves questioned the normative aspect of that conceptual framework (positive and negative contributions) because it creates misunderstandings and misleading messages depending on the perspective that is considered [73], which is further supported in [74]. Hilty and Aebischer even stress out that "the idea of ICT being either good or bad for the environment should be combated" [73], and they proposed an updated version of the framework, named the *LES model* [73]. Main changes were a shift from normative assumptions to descriptive structuring, and a better connection to production and sociological structuration theory including micro- and macro levels of abstraction.

Although imperfect, these frameworks have something in common: they are useful to structure different levels of abstraction in order to address questions related to ICT and environmental sustainability. As originally introduced by Berkhout and Hertin [15], three types of environmental effects are clearly distinguished[10]:

- *Direct* effects capture the environmental burdens generated by the production, use, and disposal of ICT equipment. This includes all the environmental effects associated with the life cycle of ICT products, ranging from raw material extraction, resource use, emissions, and management of e-wastes. These effects are focused on the technological level and are also called *first* order effects [72].
- *Indirect* effects refer to all effects that are enabled by the use of ICT, hence focusing on the application level. These effects are sometimes called *second-order* effects.
- *Structural and behavioral* effects relate to the more fundamental changes in the socio-economic system, including impacts on life styles, cultural value, and the dynamics of the economic system. They occur at a macroscopic level and are sometimes called *third-order* effects, or *other* effects. Rebound effects are classified in this category.

Rebound effect, also called *Jevon's paradox*, describes the fact that technological efficiency gains do not *de facto* lead to absolute resources or energy savings [76]. This has been illustrated in different sectors, but telling examples can be found in the field of the automotive sector [77, 78] or in the energy sector [79, 80, 48]. The dynamics behind rebound effects is complex and hard to quantify [81, 82], especially for effects which occur dynamically across space and time at a society scale [14, 75, 76]. Nevertheless, the conditions that encourage the development of rebound effects are relatively well understood [13, 76, 83, 84, 85, 86, 87, 88], e.g., policies and designs focusing only on energy efficiency, overlooking the user behavior regarding effective lifetime and effective use of the devices, end users with high incomes, high inter-connectivity, access to high quality energy such as electricity, as well as time-savings and money-savings motivations. The importance of rebound effects in digital technologies are also explicitly pointed out in the last IPCC report [35].

Once the direct environmental effects of a given ICT solution have been assessed, the natural next step is often to compare that burden with the expected benefits enabled by the solution to estimate the *net environmental balance* [12]. However, this environmental balance tends to focus on the first-order environmental

[10] This classification is somehow echoed by the *Green IT* and *IT 4 Green* definitions. In fact, the objective behind *Green IT* is to reduce the environmental impacts of IT products and services, while *IT 4 Green* aims at reducing environmental impacts in other sectors by using these IT products and services.

benefits and elude higher-order effects such as induction, rebound effects, and obsolescence [27, 76, 86, 89], which are more difficult to evaluate but clearly exist. In fact, overlooking indirect and structural effects of ICT is a recurrent shortcoming in numerous ICT environmental studies [27]. Some reports hence claim that ICT's environmental benefits can be several times greater than their own environmental burden [90]. Nevertheless, the quantification of these benefits generates a lot of controversy, as studies stress that environmental benefits attributed to the use of ICT may be overestimated [27, 91]. In addition, given this very specific ambivalent nature of ICT (and IoT) [72], the presence of unclear scopes and definitions raises concerns regarding the allocation of effects (being direct or indirect), as it can lead to double-counting issues across sectors or applications and eventually inconsistencies in the evaluation of the ICT (and IoT) environmental footprint. Redefining the scope of ICT and IoT falls out of the scope of this thesis as this should be clarified at the standardization level, but this illustrates remaining challenges associated with the considerations of environmental effects of ICT and IoT. The direct effects are generally seen as easier to evaluate as the system under study is better defined and less depending on external factors, which is discussed in the next section.

1.2.3 The carbon footprint evaluation of the ICT

In this section, we illustrate the direct effects of the ICT by focusing on its carbon footprint. As previously discussed, it is clear that a sole focus on the carbon footprint is not sufficient to capture the direct environmental effects of ICT. However, the majority of studies tend to concentrate on the evaluation of the carbon footprint because of the concerns about climate change, but also because it requires a limited effort while providing results with a reasonable uncertainty [48]. Other environmental impacts such as water consumption, toxicity, or resources depletion are reported in some reports [66, 87], but this is not systematically the case.

Freitag et al. [26] provided the most recent and detailed review of carbon footprint estimates for the ICT, including raw data analysis of existing studies and reworked estimates from the author. Figure 1.6 shows that the estimates for the ICT's emissions in 2020 vary between 1 to 1.7 $GtCO_2eq$, equivalent to 1.8%–2.8% of global GHG emissions in 2020 [26]. Obviously, these estimates carry some uncertainty but they still provide a reasonable idea of ICT footprint, even with discrepancies in the assumptions of studies. Freitag et al. [26] also propose an adjusted range to account for gaps in these studies, yielding a carbon footprint estimate of 1.2–2.2 $GtCO_2eq$ (2.1%–3.9% of global GHG emissions) in 2020. The overall share of embodied emissions and use phase emissions is respectively about 30 and 70%, albeit the embodied emissions reach about 50% for user devices. Indeed, the results show that the environmental hotspots vary from one type of product to another. For instance, the main part of the carbon footprint of servers comes from the use

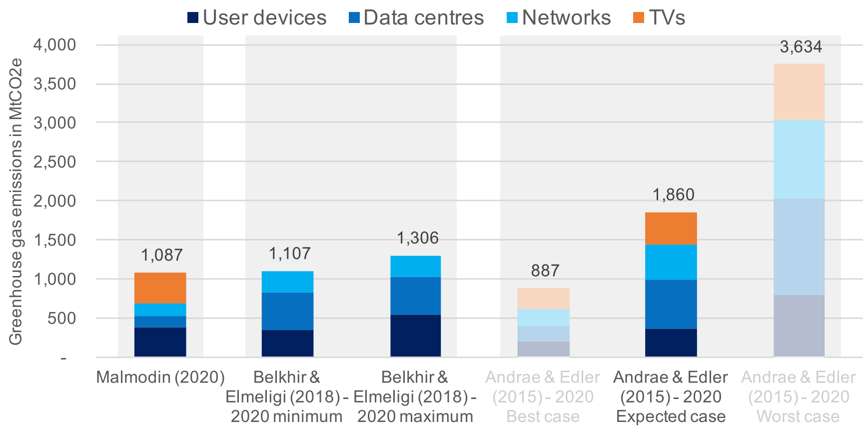

Fig. 1.6 Estimates for global ICT's carbon footprint in 2020. Figure adapted from [26].

phase which can be explained by their very intensive use in data centers over their lifetime. On the other hand, the production of electronic devices can represent a significant part of the environmental impacts, especially for end-user (mobile) devices. This is even reinforced by the important efficiency improvements during the use phase and the increasing use of low-carbon energy [92]. For instance, the embodied carbon footprint of smartphones accounts for more than 70% of the overall carbon footprint [19, 20].

1.2.4 The case of IoT

None of the existing studies evaluating the carbon footprint of ICT includes the carbon footprint of IoT devices. However, according to CISCO, "a growing number of M2M applications [...] are contributing in a major way to the growth of devices and connections" [3], as depicted in Fig. 1.7. CISCO also highlights that this trend is "accelerating the increase in the average number of devices and connections per household and per capita[11]". They evaluated that by 2023, M2M connections will be half of the total devices and connections worldwide, hence becoming the fastest-growing category during the forecast period (+19%/year), before smartphones. The IoT is therefore expected to contribute like no other emerging ICT trends to the growth of ICT's emissions, as shown in Fig. 1.8. In particular, ICT user devices are already responsible for an important share of the current ICT footprint, approx-

[11] In fact, CISCO shows that the number of devices and connections is growing faster (+10%/year) than both the population (+1%/year) and the number of Internet users (+6%year).

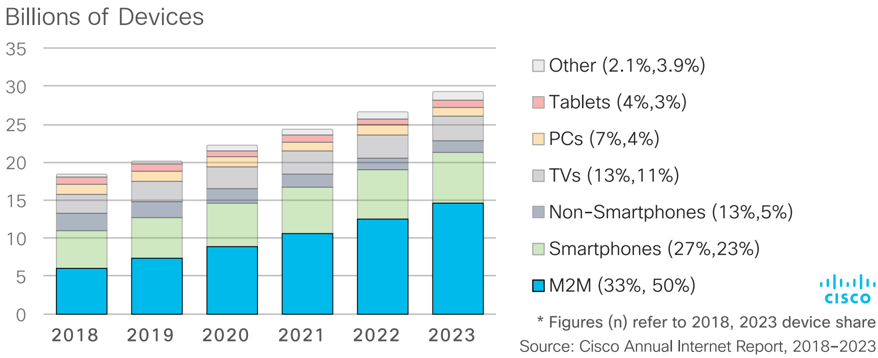

Fig. 1.7 Global devices and connection growth, adapted from [3]

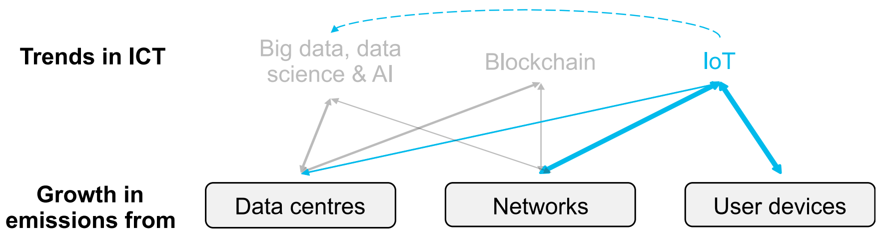

Fig. 1.8 Qualitative estimated impacts that trends in ICT have on ICT emissions growth. Figure adapted from [26].

imately between 30 and 50% depending on studies [26, 27] (excluding the footprint of IoT devices). Furthermore, a significant part of the current ICT footprint is attributed to the production (estimated between 281 and 543[12] $MtCO_2eq$ [26] in 2020). This clearly highlights why more attention should be paid to the environmental footprint of the IoT, including life-cycle phases from the production to disposal.

Beyond the environmental impacts generated over their life cycle, the deployment of an IoT solution may also lead to induction and obsolescence effects, e.g., by inducing transportation to maintain the IoT infrastructure and by making older systems obsolete if they are not compatible or less appealing. One could also think about a *buzzword* effect which may drive new products to include emerging technologies in order to be branded as *high-tech* [CP4]. IoT can also be fertile ground for rebound effects that are likely to be significant in digital technologies [76], as pointed out in the last IPCC report [35]. Finally, the expanding dependence on digital tools and services can be seen as an emerging risk [70].

[12]Freitag et al. [26] reports that "[...] roughly 23% of ICT's total footprint is from embodied emissions, yet the share of embodied emissions for user devices specifically is around 50%".

On the contrary, it is also important to point out the indirect effects of IoT, which may enable optimization and substitution effects at the application level. For instance, IoT could support remote control and predictive maintenance (thus reducing the need for human intervention and the associated environmental burden), and efficiency improvements in essential systems including food, water, transportation and energy. IoT could also foster the transformation towards more sustainable patterns of production and consumption by supporting the tracking and transfer of information related to a specific product across value chains, through digital twins and digital product passports for instance.

Although the direct effects of IoT may seem more straightforward to evaluate than the indirect or structural effects as they are more tangible, the body of literature addressing these concerns remains limited. Previous works have already been initiated on the evaluation of the energy consumption of connected devices while considering the multi-operating modes of IoT devices such as active and sleep modes [31, 32]. However, the direct environmental effects associated with the production (and end-of-life) of IoT devices were vastly under-explored at the time we started working on this topic[13] [18, 32, 31, 71, 93]. Because IoT devices are made up of electronic components, the environmental impacts of producing the IoT are closely related to the ones of electronic devices and semiconductors. This therefore includes a multitude of raw materials, complex supply chains all across the world, and high-tech manufacturing processes [94, 95][JP2]. To support a comprehensive analysis of the direct effects of IoT, the well-known LCA methodology is often pointed out, which we introduce in the next section.

1.3 Life cycle assessment (LCA)

This section provides the fundamentals regarding the LCA methodology. It is predominantly based on the reference book *Life Cycle Assessment–Theory and Practice* [51] and the *International Reference Life Cycle Data System (ILCD) handbook* from the European Commission [17].

1.3.1 Definition and main characteristics

LCA is a structured, comprehensive and internationally standardized methodology to quantitatively evaluate the *potential* environmental impacts of a product (a

[13] A state of the art is provided in the first part of this thesis, in particular in Chapters 2 and 4.

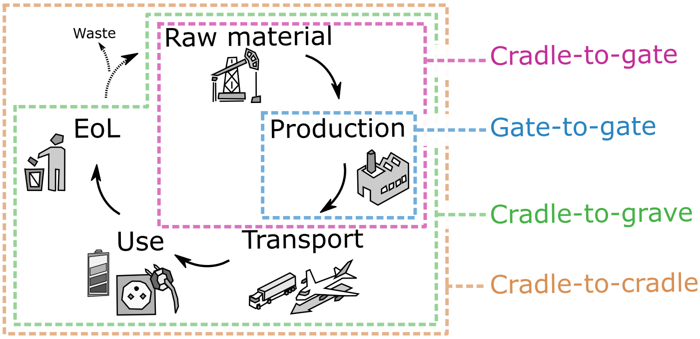

Fig. 1.9 Illustration of the life-cycle phases, from raw-material extraction, to production, use, and finally the end of life.

good or a service) throughout its whole life cycle including raw-material extraction, production, use, and finally the end of life. This engineering methodology supports the quantification of all relevant emissions and resources consumed by the product, together with the associated environmental and health impacts or resource depletion issues [17].

LCA is generally used for different goals, including for instance environmental communication, decision making, and product improvement (i.e., *eco-design*) [51]. It is widely recognized as a very useful methodology to (i) show "how a specific functionality can be achieved in the most environmentally friendly way among a predefined list of alternatives", or (ii) to "show in which parts of the life cycle it is particularly important to improve a product to reduce its environmental impacts" [51].

LCA hence offers a multi-indicators assessment of environmental impacts, which helps to avoid (or at least identify) *shifting the burdens* from one impact to another. This *problem-shifting* phenomenon is clearly to be considered, as it resolves one environmental problem while creating others [17, 48]. This is an important feature of LCA, especially nowadays as climate change receive most attention while being one environmental issue among others, yet very important. Other issues include for instance water consumption, land occupation and transformation, aquatic and terrestrial eutrophication, ecotoxicity, and the depletion of non-renewable resources such as minerals or fossil fuels [51]. Another key characteristic of LCA is to take a life cycle perspective where several phases of the life cycle's product can be included, as illustrated in Fig. 1.9 different possible study boundaries, e.g., *gate-to-gate*, *cradle-to-gate*, *cradle-to-grave*, and *cradle-to-cradle*.

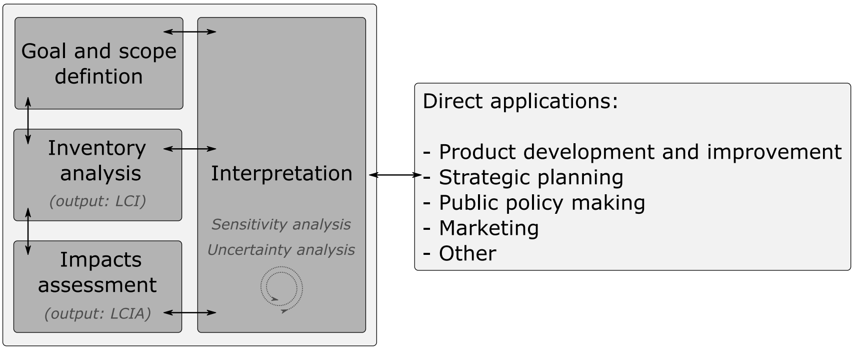

Fig. 1.10 Main methodological phases in the framework of LCA. Figure adapted from [16, 51].

1.3.2 Main methodological phases of LCA

The LCA methodology is composed of four main phases, i.e., (i) goal and scope definition, (ii) inventory analysis, (iii) impact assessment, and (iv) interpretation, as described in the ISO14040 standards series [16]. We detail the characteristics of each phase below.

The **goal and scope definition** is the very first phase of an LCA. The goal definition mainly states why the study is performed, what question it is intended to answer, and for whom it is performed [16]. Defining the scope of the study includes, among others, the definition of the product system and the system boundaries, the functional unit, the allocation procedures[14], the geographical and temporal boundaries, and the assumptions [16]. These information should be clearly mentioned, as it can have a strong influence on the validity of the conclusions and recommendations based on the results of the LCA. The functional unit[15] requires specific attention as it provides a reference to which the inputs and outputs of the LCA are related, which directly influences the reference flow of the product used in the next phases.

[14] Allocation is an approach to solve multifunctionality in LCA, where multifunctionality characterizes a process which provides more than one function [17]. Allocation consists in partitioning input and outputs flows of the product under study between the co-functions based on a pre-defined *allocation key* [16, 17]. Although guidelines state that allocation key should be based on "common causal physical relationships between the co-functions" [17], defining the most appropriate allocation key is far from being trivial in practice. The allocation could also be performed according to another relationship between the co-functions (e.g. economic relationship), although the robustness is decreased [17].

[15] The functional unit is defined as "a quantitative description of the function or service for which the assessment is performed" [51].

The **inventory analysis** corresponds mainly to the collection of information and data for the physical flows including inputs (e.g., resources, energy, materials, etc.) and outputs (e.g., emissions, wastes, products, etc.). All processes involved in the product system should be studied, in accordance with the reference flow of the product defined by the functional unit in the goal and scope definition. Most of the time, this phase relies on a combination of both primary and secondary data[16]to model the foreground and background systems[17]. At the end of this phase, a list of quantified elementary flows associated with the product is obtained. This list is called the life cycle inventory (LCI) and it is used in the next phase.

The **impact assessment** is the third phase of the LCA and it can be seen as a translation phase. In fact, all the physical flows from the LCI are translated into *potential* impacts on the environment based on models from environmental sciences. As explained in [51], "the models of the relationships between emission (or resource consumption) and impact are based on proven causalities [...], or on empirically observed relationships [...]". In practice, this phase is mainly automated by LCA software, based on LCIA methods such as ReCiPe, CML, or IMPACT 2002+, among others. The life cycle impact assessment (LCIA) phase consists of five steps as illustrated in Fig. 1.11, although the two last ones are optional according to the ISO 14040 standard [16]:

1. The *selection* of the impact categories in accordance with the scope definition. This includes the selection of a set of representative indicators and their associated method for each impact category.
2. The *classification* of elementary flows from the LCI to the selected impact categories. This a qualitative step aiming at identifying all the relevant elementary flows for a given indicator. In other words, it tackles the question "*which* impact categories does each LCI result contribute to?" [51]. If i is the index of elementary flows E in the LCI, i_c gathers all i such that E_i contributes to the category c, or equivalently

$$i_c = \{i | E_i \quad \text{contributes to} \quad c\}.$$

3. The *characterization* step quantifies to what extent the elementary flows impact the category, if they were classified in this category. It therefore tackles

[16] Primary data is obtained through specific unit process data measurements or information directly taken from producers of goods or operators of processes and services [17]. On the contrary, secondary data is usually taken from third-party database providers and can be either, specific, generic or averaged data [17].

[17] The foreground system is defined as "the processes of the system that are specific to it" while the background system relates to "the processes, where due to the averaging effect across the suppliers, a homogenous market with average (or equivalent, generic data) can be assumed to appropriately represent the respective process" [17].

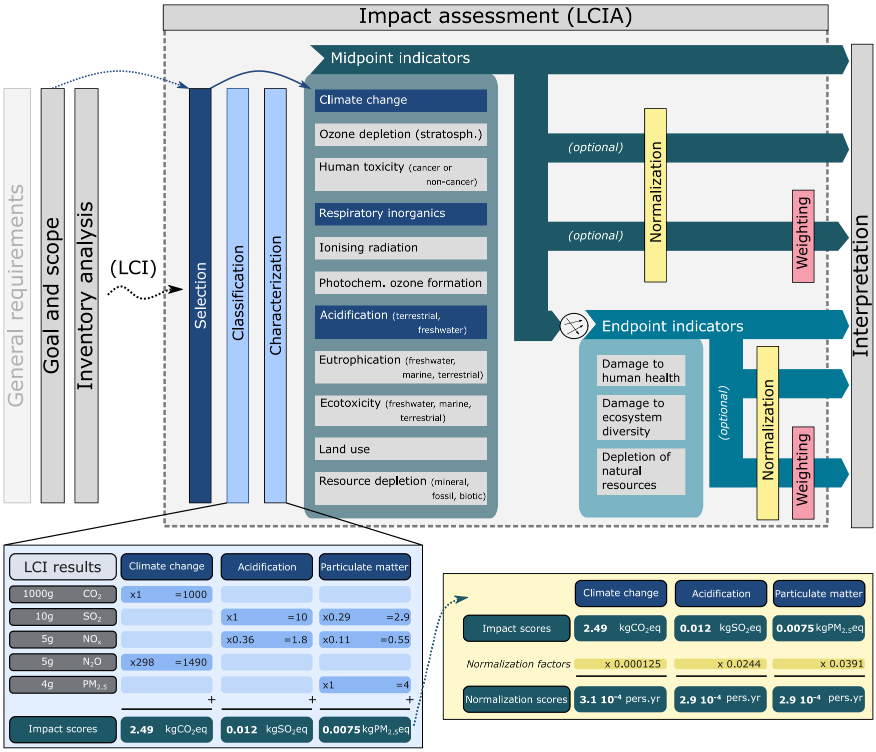

Fig. 1.11 Conceptual illustration detailing the different steps of the impact assessment. The illustration is adapted from [51, 17].

the question "*how much* does each LCI resut contribute?" [51]. The impact score[18] (IS) for an impact category c is obtained by multiplying elementary flows E by their associated characterization factor (CF), and summing over all relevant interventions i_c [51], as shown in Eq. 1.2:

$$IS_c = \sum_{i_c} (E_{i_c} \cdot CF_{i_c}). \tag{1.2}$$

The characterization factors are based on environmental models and the characterization results in a given impact category are expressed with a single common metric. Each category has its own metric. This allows for the aggregation of all sub-contributions into one same unit for the category and explains the presence of the *equivalent* (*-eq*) suffix in the unit of an impact cat-

[18]The impact score can also be called characterization result, characterization score, or characterized result.

egory. The characterization step can be done at two levels, known as *midpoint* and *endpoint* levels. They differ in their objective. An impact assessment at the midpoint level aims at evaluating the contribution of elementary flows according to specific impact categories with a clear environmental meaning whereas the endpoint level is used to model a *damage* on human health, ecosystem, or resources. Endpoints indicators are further down the cause–effect chain of the environmental mechanism and are obtained by the combination of midpoint indicators [51], as illustrated in Fig. 1.11. For instance, the climate change category lies at the midpoint level (expressed with the GWP in $kgCO_2eq$[19]), and it is used among other impact categories to evaluate the damage on human health and natural environmental at the endpoint level. The characterization step is important as it reduces the LCI to a manageable subset[20] of indicators with a well-defined environmental meaning [51]. Most often, LCA studies stop after the characterization step.

4. (optional step) The *normalization* step can be used to compare characterization results with a reference situation, which gathers a common set of reference impacts usually defined in the LCIA methods by normalization factors (NF). The reference situation usually captures the impacts of one person during a year, hence expressed in person equivalent. The normalization scores (NS) are obtained by multiplying the impact scores from the characterization step with the normalization factors category-wise, as shown in Eq. 1.3:

$$NS_c = IS_c \cdot NF_c. \tag{1.3}$$

The normalization result is hence dimensionless. The normalization step can provide additional information for the interpretation, or for comparison. The normalization step can be applied both at the midpoint or endpoint levels.

5. (optional step) The *weighting* (or *grouping*) step aims at simplifying the interpretation of the results by combining several impact categories together towards one single environmental score. The weighting score (WS) is the weighted sum of the normalization scores[21] with the associated weights w_c for each impact category, as shown in Eq. 1.4:

$$WS = \sum_c (NS_c \cdot w_c). \tag{1.4}$$

The choice of the weights w_c is arbitrary. It therefore introduce value judgment in the LCA results as a relative importance is given to each impact category, which was not the case in the previous steps. For this reason, the ISO

[19] GHG emissions can be quantified according to different time horizons, e.g., 20-year or 100-year GWP.

[20] In fact, the LCA can gather hundreds of flows and is hence difficult to read and understand for humans.

[21] Note that some weighting methods do not need a preceding step of normalization as they directly include a normalization part within the weighting step [17].

standard prohibit this last step in "LCA studies intended to be used in comparative assertions intended to be disclosed to the public" [16]. Although the weighting score may simplify communication as it is the case for eco-label for instance, this also degrades the usefulness of multi-indicators analysis. Moreover, this can hide *problem-shifting* issues, depending on the weights that have been defined.

Finally, the **interpretation** phase aims at analyzing the results of the study to answer the question(s) raised in the first phase, while respecting the definition of the goal and scope. A thoughtful interpretation analyzes and discusses the LCI and the LCIA, although the focus is usually made on characterization results. If normalization and weighting were carried out, they should also be included in the interpretation.

In practice, conducting a complete LCA is always an iterative process, requiring numerous feedback loops before converging towards the final results [17, 51]. The use of sensitivity analysis along the process can help identifying assumptions and data requiring additional work or attention, to ensure robust results and conclusions [51]. This is further discussed in the next section.

1.3.3 Uncertainty, variability, and sensitivity

The presence of uncertainty in LCA is a fact, which is well acknowledged by the LCA community and the standards [16, 17, 51]. However, several misconceptions around the concepts and the sources of uncertainty exist, therefore requiring a clarification of the basic terminology around key concepts such as uncertainty, variability, sensitivity, precision, and accuracy. The clarifications provided in this section are predominantly taken from the LCA reference book from Hauschild and colleagues [51], providing deliberately simplified definitions for LCA practitioners rather than specific statistical concepts.

Uncertainty refers to "everything we do not know and we cannot be certain about, regardless whether we are aware of it or not" [51]. Uncertainty is hence somehow describing "the degree to which we may be off from the truth" [51]. However, as it is inherently impossible to obtain this *ground truth*, it is hence impossible to properly define to which degree we are off from it. Instead, *reference points* are therefore defined in practice (e.g., a measurement), by assuming that they are close from that *ground truth* [51]. In LCA, uncertainty can be related to different sources, ranging from uncertainty in the input data to uncertainty in the choices made by the analyst [96]. Although there is no unique and exhaustive classification of uncertainties in LCA, Hauschild and colleagues [51] propose a clear overview of different sources of uncertainties. A simplified version is provided in Table 1.1.

Table 1.1 Classification of sources of uncertainty and variability in LCA. This Table is adapted from [51].

Uncertainty type		Brief description or example
Variability	Temporal variability	Inherent variations in the studied system, e.g. seasons
	Spatial variability	Inherent variations in the studied system, e.g., population density and climate conditions
	Variability between objects	Inherent variations in the studied system, e.g., difference in technologies for the same product
Parameter uncertainty		Inaccuracy, variability, uncertainty, lack or non-representativeness of input data and model parameters
Model uncertainty	Model structure uncertainty	Algorithms in process and characterization models, uncertainty in the model itself (variables, equations, linearity, ...)
	Uncertainty due to choices	Definition of system boundaries, choice of allocation methods
Scenario uncertainty		Definition of functional unit, selection of LCIA method(s), and choice of normalization reference system
Epistemological uncertainty		Lack of relevant knowledge
Mistakes		Choosing the wrong substance or process due to similar names as references, unit conversions or unclear units like tons vs. metric tons/tonnes
Relevance uncertainty		Environmental relevance, accuracy or representativeness of an indicator towards an area of protection

Variability refers to the "spread in the data that will always be observed" [51]. The variability can therefore be measured and quantified, but it can never be reduced as it is inherent to the observed phenomenon and to its natural variance. As shown in Table 1.1, Hauschild and colleagues [51] differentiates three types of variability in the context of LCA, i.e., temporal variability, spatial variability, and variability between objects.

Sensitivity describes "the extent to which the variation of an input parameter or a choice leads to variation of the model result" [51]. Intuitively, a model is said to be sensitive to a parameter if applying a small perturbation in this parameter causes a large change in the model results [51]. Although there is no general consensus on the exact definition of the term sensitivity in the literature [51], two main types of sensitivity analysis are usually pointed out, namely local and global sensitivity analysis (LSA and GSA, respectively) [96]. In a LSA approach, a perturbation is applied to one single input of the model whereas in a GSA approach, the analysis aims at understanding "how the uncertainty in the output of a mathematical model can be apportioned to different sources of uncertainty of its inputs" [96]. The joint analysis of both uncertainty and sensitivity ensures the best completeness of input data and robustness of the output results [51].

Finally, the difference between accuracy and precision should also be clarified in the context of LCA, as these two terms are often used interchangeably albeit they are different. **Accuracy** refers to the correctness of what we are aiming to evaluate while the **precision** refers to "the quality of being reproducible in amount or performance (i.e. any repetition of a calculation, experiment, model run, etc)" [51]. The precision of a model could hence be low whereas its accuracy is high, and inversely.

In practice, uncertainty is addressed in different ways among LCA studies, ranging from no consideration at all to extensive uncertainty analysis even if this is rare. The presence of uncertainty is often pointed out as an important limitation discrediting the use of LCA and questioning the validity of the results and their interpretation. Yet, acknowledging, understanding and properly managing uncertainties in LCA allows for more robust results and conclusions [51], which is by far a better approach than simply ignoring the presence of uncertainty. Although it is difficult to comprehensively account for all sources of uncertainty given the wide variety listed in Table 1.1, it is at least important to explicitly state what forms of uncertainty are considered (and how) but also what are the ones that are overlooked in the analysis.

1.3.4 Main modeling approaches and principles

The three most common assessment approaches are the bottom-up, the top-down and the hybrid one [51, 97, 98, 99, 100]. The **bottom-up approach** is used in process-based LCAs and consists in modeling the overall impacts of the product by aggregating the impacts generated by its sub-components. In other words, the product is modeled by linear sums of sub-component processes [18]. This approach has the potential to be very precise but it is time-consuming and is known to suffer from the truncation error [18, 101, 102], resulting in a potential underestimation of the environmental impacts. The truncation error is a practical limitation which prevents the modeling of all activities and variables such as effective idle time, tests and maintenance, or interactions with other activities while maintaining a finite study boundary [18, 98, 101]. On the contrary, the **top-down approach** uses macroscopic data collected at the industry level, e.g., economic input-output (EIO) analysis [94, 103]. This eludes the truncation error but also prevents an in-depth understanding of processes included in the results and usually leads to higher results than process-based LCAs. The **hybrid approach** combines both bottom-up and top-down approaches which is often considered as the most accurate by experts [18, 101, 104], although it imposes more data requirements. As the assessment method influences the results, it must be clearly identified [104, 101].

Aside from these three main LCA approaches, there are mainly two modeling principles for LCA, respectively known as **attributional** and **consequential** modeling [51, 105, 106]. Although there is still ongoing debates in the LCA community regarding these two types of LCA [105, 107, 108], the key difference between attributional LCA (ALCA) and consequential LCA (CLCA) is that the former attempts to assess what environmental burdens can be associated with a product whereas the latter attempts to assess the environmental burdens that will occur, directly or indirectly, as a consequence of a decision (usually represented by changes in demand for a product) [106]. ALCA is the most common practice since the development of LCA in the mid-nineties. This modeling principle assumes that the product system is isolated from the rest of the technosphere or economy [51]. In addition, it assumes the use of average supply chain processes as *best estimates*, i.e., the use of *market mix*. Let us mention that in the context of ALCA, allocation is used to solve multifunctionality [17]. The modeling principle for CLCA rather aims at considering the introduction of the product system and its consequences, including (future) changes to economy and supply chain [51]. Albeit the main differences in modeling occur during the LCI, CLCA requires a much better understanding of the economic system and the dynamics between the supply chain. This is hence calling for knowledge outside of conventional engineering, which has been historically at the core of LCA [51]. Moreover, CLCA is usually associated with significantly higher level of uncertainty and more modeling complexity, which can makes it less attractive for LCA practitioners.

1.3.5 LCA tools and databases for electronics and semiconductors

The ISO international standardization [16] remains mainly focused on the description of the methodology at a theoretical level [51]. The European Commission did improve the situation in 2010 by providing the ILCD handbook together with a guide to support LCA practitioners and improve standardization [17]. Even if it helps regarding the questions "what to do?" and "how to do?", gaps still exist in practice. This is especially the case for LCA of electronic devices and systems because they rely on very specific products and processes requiring highly advanced technologies intertwined in a complex supply chain. In order to provide more recommendations to carry out the LCA of ICT products or services, additional guidelines and recommendations have been published by the European Telecommunications Standards Institute (ETSI) [109] and the International Telecommunication Union (ITU) [72] over the last decade. These can support the implementation of LCA on ICT products or services. Yet, to the best of our knowledge, there are no specific guidelines regarding LCA for IoT. Consequently, LCA of IoT systems is generally carried out by using the existing guidelines, tools and databases dedicated to electronics and ICT. Obviously, trade-offs clearly exist with respect to data resolution and quality, complexity, and accessibility. The choice is generally done depending on (i) the goal of the LCA, (ii) the expertise of the LCA practitioner, (iii) and the time and (financial) resources available for the study.

This section therefore provides two non-exhaustive lists regarding the different tools (software and databases) that can be used in the context of the IoT. An overview of the currently most used LCA software and databases for electronics is provided in Table 1.2 and Table 1.3. Other databases are also provided in [51] but the majority does not cover components or processes related to electronics. In both tables, the qualitative evaluation has been done based on authors' prior knowledge and expertise. The best state-of-the-art databases regarding LCA of electronics are Sphera LCA[22] (Extension XI) Electronics, EIME database, Negaoctet, and ecosystem. Both tables clearly show that although some LCA software are open source, all advanced state-of-the-art and specific databases for electronics remain proprietary. In practice, this significantly limits the development of consolidated models shared among the community. It is often very difficult to obtain up-to-date and relevant data, due to strong confidentiality concerns and the fast-developing pace of semiconductor technology leading to a general important lack of primary data [97, 110, 111]. This is further emphasized by the major use of proprietary LCA software and databases in currently available LCA. In this thesis, we use the Sphera LCA software together with the professional and Extension XI (Electronics) databases [112], for their high level of details on electronic components and its extensive documentation.

[22] Sphera LCA was previously called GaBi.

Table 1.2 List of software for performing LCA (non-exhaustive).

	Expertise needed	Open source	Sensitivity analysis	Scriptable
Sphera LCA (Sphera)	+++	✗	✓	✗
SimaPro (PRé Sustainability)	++	✗	✓ †	✓
EIME (Bureau Veritas)	++	✗	✗	✗
OpenLCA (GreenDelta)	++	✓	✓	✓
Brightway2	++	✓	✓	✓
Umberto (iPont)	?	✗	?	?
Excel	+	✓	✓	✗

† : Depending on the licence type.

Table 1.3 List of databases including electronic-related products or processes (non-exhaustive).

	Resolution	Documented	Open source	Multi-indicator	Specific to electronics
Sphera LCA† (Sphera)	+++	+++	✗	✓	✓
Negaoctet	+++	++	✗	✓	✓
EIME database (Bureau Veritas)	++	++	✗	✓	✓
ecoinvent	++	+++	✗	✓	✗
ecosystem	++	++	✓	✓	✓
Ansys/Granta	+	++	✗	✓	✗
Base carbone (ADEME)	+	++	✓	✗	✗

† : Extension XI Electronics

PART I
Towards systematic LCA to evaluate the direct environmental effects of the IoT

2

A framework based on hardware profiles to streamline the carbon footprint evaluation of IoT edge devices

A journey of a thousand miles begins with a single step.
– Lao Tzu

ALTHOUGH the literature on the environmental footprint of ICT devices and services has grown over the last years, the environmental effects of IoT devices have been far less studied and are consequently often overlooked. In fact, even if general LCA methodologies for IoT already exist, quantitative results are still scarce and few or none information are currently provided to support this evaluation [26]. The lack of comprehensive study on the (embodied) footprint of IoT is also stressed in [18, 32]. However, as introduced in Chapter 1, the production of

ICT end-user devices is currently pointed out as a significant contributor to the ICT carbon footprint [27]. It is hence critical to evaluate the direct environmental effects of IoT, especially because it relies on the massive deployment of electronics devices.

The first step of this thesis therefore focuses on the production phase of IoT devices. We focus on consumer IoT edge devices such as connected objects, smart wearables, and smart sensors which have been pointed out as the main contributor to the rising number of IoT devices [3], but this chapter can also serve as a basis for industrial IoT (IIoT) devices, Industry 4.0 (I4.0) applications and other *smart*-related applications. Rather than concentrating on a single specific IoT device, we aim at considering a wide variety of devices to capture the inherent variability of IoT designs. We propose a parametric quantitative framework based on hardware profiles to streamline the carbon footprint evaluation of a multiple IoT devices, and compare the results of four case studies with the environmental reports available from Google and Apple.

This chapter is organized as follows. First, we conduct an analysis of the state of the art in Section 2.1 to highlight the lack of environmental assessment in the context of IoT. Then, Section 2.2 describes the methodology used to build the proposed framework. We present the concept of *hardware profiles* for IoT devices and we detail the model supporting the quantitative framework. Next, Section 2.3 presents the results of the framework and illustrates its use on four case studies, i.e., an occupancy sensor, a drone, a connected home assistant, and a smart watch. Finally, Section 2.4 discusses the limitations of the framework, provides a comparison with existing studies, and discusses the uptake of the framework in the literature since its publication.

2.1 Context

This section contextualizes the objectives of this chapter with respect to the state of the art.

2.1.1 Related Works

Qualitative life-cycle models for generic IoT devices are proposed in [113, 114] but even though they are helpful for a better understanding of the different key steps in the life cycle of an IoT device, they do not provide quantitative results to model the direct effects of IoT devices. Similarly, environmental concerns associated with the development of IoT technologies are stressed in [115, 29] although it is not built on LCA results.

Several studies attempt to consider the environmental burden generated by the IoT devices in specific applications but they usually use over-simplified modeling mainly because of the high complexity of electronic devices and the lack of data. For instance, [116, 117, 118, 119] have questioned the environmental consistency of multi-functional home energy management system (HEMS) by including the additional life-cycle impacts arising from the introduction of the connected layer itself and not only all the potential savings generated. Although quantitative results are provided, the lack of details and the relatively old publication date with respect to the faste evolution of IoT technologies limit the reusability. It also illustrates that assessments are sometimes done by scaling a reference common product, e.g., the printed circuit board (PCB) of a laptop mainboard, which is most likely not representative of the actual HEMS hardware. More specific analyses are carried out in [120, 121] which point out the difficulty to quantify the environmental impacts of IoT in emerging applications such as smart textiles [122]. However, it can be seen in their supplementary material that integrated circuits (ICs) have not been considered nor magnets in the vibration motor, similarly to [119]. Moreover, ecoinvent and Idemat databases have been used in these studies even though they are often pointed in the literature as not well suited for LCA of electronics [19, 20]. This is also the case in [123] for LCA of cardiac monitoring devices, or in [124] for the LCA of a textile-based large-area sensor system where only a single *eco-costs* indicator is used with no LCA detail. Another study [122] proposes environmental considerations for smart textiles with the eco-costs indicator. A simplified LCA is carried out in [125] where embodied energy and carbon footprint are considered for the eco-design of electronic-based water sensors. Although not perfect, these are interesting attempts to better account for the additional impacts due to the presence of electronic components.

Typical breakdowns of the carbon footprint for IoT device are given in [46], with respect to hardware components such as PCB, ICs and batteries. The results are mainly based on literature data and the authors highlight that application-awareness is critical in semiconductor LCA [126]. Similarly, the authors in [127] underline the necessity to adopt a system-level perspective and propose a methodology to assess the direct environmental effects of wireless sensors (WSN) networks. They conclude that energy consumption of WSN devices is of primary importance. However, even if edge devices seem to be responsible for the main part of the impacts, hardware is quickly described especially for electronics which is simply described by total mass. More generally, the low resolution on electronic components is therefore a bottleneck that must be addressed. Lelah et al. [93] also carried out the LCA of a complete WSN system with heterogeneous power sources but the results clearly show that the manufacturing phase dominates. Yet, the results are all provided as a share of the total impacts within each impact category (including GWP), which can be sufficient to conduct eco-design on the solution but hinder the re-uptake and comparison of the results. The challenge of eco-design in the IoT context and the complexity of shared infrastructures is also pointed out in [128]. They motivate that the life-cycle model of an IoT system should include sensing, edge and cloud devices together with a representation of the hardware components. However, no quantitative results are provided for the case study in the study, which is improved in the author's PhD [45] for two impact categories including GWP. Nevertheless, the work focuses on specific case studies and the quantitative results can hardly be generalized to a wide variety of IoT devices. Bonvoisin et al. [129] proposes an integrated framework supporting the design of environmentally-sound ICT-based optimization services. Carbon footprint and resource depletion results are given for each WSN but no more details are available which makes comparison and re-uptake difficult. In their LCA focusing on the specific case study of smart smoke detectors, Manz et al. [130] evaluated the environmental footprint of the IoT hardware with SimaPro and ecoinvent over several indicators. Yet, they acknowledged that several electronic components where not included in the study, e.g., the acoustic alarm siren, a connector, the communication modules, and some ICs.

This analysis of the literature reveals three main gaps. First, even though general methodologies already exist, quantitative results are still scarce: few LCA are available for assessing the direct environmental effects of the IoT. Then, the discrepancies between scopes and data strongly complicate systematic LCA studies and results comparison, worsened by the general lack of details on hardware components and modeling assumptions. This highlights the relevancy of a generic yet detailed framework, which is further supported in [18] pointing out that integrated analyses or meta-analyses are of greater utility than point estimates. Finally, the task is even more difficult in the case of IoT, as it gathers heterogeneous IoT devices for many different applications in a fast evolving technological field. All these factors complicate the evaluation of the direct environmental effects of IoT devices.

2.1.2 Objectives

To bridge these gaps, the goal of this chapter is to provide a quantitative framework based on the LCA methodology to streamline the carbon footprint evaluation of multiple IoT products simultaneously under similar boundaries. The first objective of this chapter is hence to design a framework that can be applied to a wide variety of IoT devices. It must provide a streamlined evaluation of the carbon footprint while keeping a high level of details regarding modeling assumptions. Then, the second objective is to estimate the variability existing between the carbon footprint evaluation of a variety of IoT devices. Finally, the general framework has to be applied to specific existing IoT case studies to demonstrate its effective use and validate the results with the few existing studies.

2.2 Methodology

This section describes the methodology and the modeling assumptions used to develop the framework. Since it is infeasible to consider every IoT design for every IoT application and since performing a single LCA for a specific IoT device would not be representative of the high diversity of designs and applications in this field, we introduce a framework that aims at streamlining the cradle-to-gate carbon footprint evaluation of several IoT devices. To tackle this complexity, we propose a bottom-up approach based on IoT *hardware profiles*.

2.2.1 Hardware profiles

In our framework, an IoT hardware profile is the description of an IoT edge device in terms of *functional blocks* and *hardware specification levels*. The **functional blocks** can be understood as categories gathering components that are involved in the implementation of a common function such as sensing, connectivity, or power supply of the IoT edge device. The definition of each functional block is provided in Table 2.1 and the general architecture of an IoT edge device expressed in terms of functional blocks is presented in Fig. 2.1(a). It has been inspired by ETSI [109] and ITU [72] standards for the LCA of ICT equipment even though we do not claim full compliance due to the parametric nature of our approach.

Table 2.1 Description of functional blocks.

Functional block	Description
Actuators	Components that physically act on the environment
Casing	Structural components of the IoT edge device whose primary function is to protect the electronic components
Connectivity	Components which are involved in data transmission
Memory	Components involved in the data storage on the IoT edge device
Others	The rest of the components which do not fit another *functional block*
PCB	Components responsible for the electro-mechanical support and electrical connections between electronic components of the IoT edge device
Power supply	Components involved in the energy source and power management of the IoT edge device, which could be battery-powered or mains-powered
Processing	Components involved in the data processing and control tasks on the IoT edge device
Security	Components related to cryptography and protection of sensitive data
Sensing	Components involved in measuring physical quantities of the environment
Transport	Related to the shipping of the assembled IoT edge device from the factory to the consumer
User interface	Components allowing interactions between external users and the IoT edge device

The core idea behind IoT hardware profiles is to leverage the similarities between IoT edge devices through functional blocks while maintaining some versatility, as their hardware complexity varies from one device to another depending on exogenous factors such as the required performances for the application or the user requirements. Therefore, the content of each functional block is further specified with four levels of hardware complexity, called the **hardware specification level (HSL)**. In other words, the HSL is an image of the functional complexity of the block that defines its internal hardware architecture to implement the functionality. Table 2.2 provides the details for each HSL, which can then be used to define hardware profiles, as shown in Fig. 2.1(b). The different HSL are based on the analysis of several existing IoT edge devices and IoT designers and companies have also been consulted to discuss the framework. While Table 2.2 is not exhaustive, it can already covers a wide variety of current IoT edge devices. Other classifications of IoT exist [131] but they are usually more focused on IoT applications rather than on the hardware itself, as suggested in [4, 132, 133].

LCA has then been carried out in the Sphera LCA software for each HSL to provide the associated carbon footprint. The total carbon footprint of a given hardware profile is eventually given by the sum of the carbon footprint contributions of each functional block, as illustrated in Fig. 2.1(c). The result of the framework is therefore uniquely defined by the hardware profile of the IoT edge device. This can therefore be used to streamline the carbon footprint evaluation of a variety of IoT edge devices.

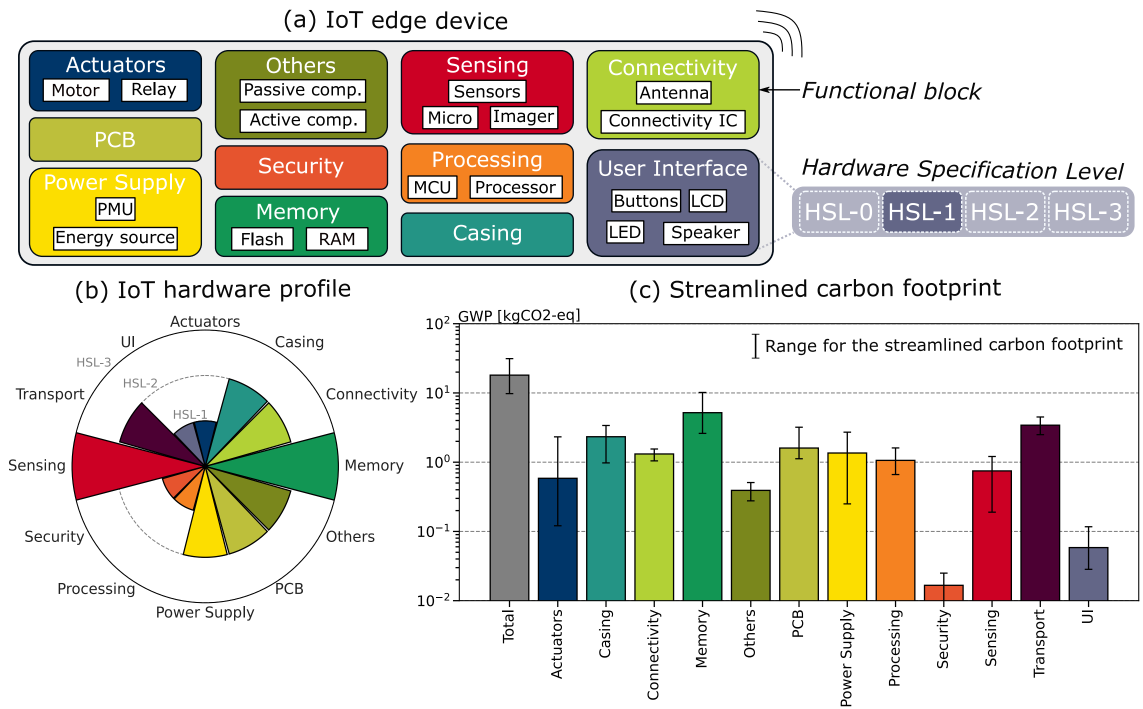

Fig. 2.1 (a) The general architecture of an IoT edge device with the concept of functional blocks and HSL, (b) an example of IoT hardware profile, (c) the resulting streamlined carbon footprint evaluation obtained by the framework for the hardware profile in (b).

Table 2.2 Detailed bill of material for IoT hardware profiles. For each *hardware specification level*, lower/typical/upper parameters considered are given. If not mentioned explicitly, all data is taken from Sphera LCA professional and Sphera LCA Extension XI (Electronics) databases. All the modeling is carried out in the Sphera LCA software. Additional details are provided in Appendix A.

Funct. Block	Hardware Specification Level (HSL): HSL-0	HSL-1	HSL-2	HSL-3
Actuators	No actuator	Vibration motor (1g) 1/2/4	Relay (SSR) 1/2/4	DC motor (50g) 1/4/6 Motor driver ‡ 1/2/5 mm^2 Motor driver transistor 1/4/6
Casing	No casing	ABS plastic granulate 10/50/100 g Aluminium 1/10/30 g Steel 1/10/30 g	ABS plastic granulate 200/400/500 g Aluminium 20/80/150 g Steel 20/80/150 g	ABS plastic granulate 700/800/900 g Steel 70/160/300 g
Connectivity	Embedded in *Processing* (share of the die area) Printed antenna (embedded in *PCB*)	Connectivity IC * 5/10/20 mm^2 Printed antenna (embedded in *PCB*)	Connectivity IC ▲ 20/30/45 mm^2 External whip-like antenna 10/15/30 g	Connectivity IC ▲ 45/50/60 mm^2 External whip-like antenna 10/15/30 g
Memory	Embedded in *Processing*, Flash + RAM ($\simeq$ kB)	DRAM †† (32/128/512 MB) 2/7.9/31.5 mm^2 Flash † (32/128/512 MB) 0.2/0.8/3.2 mm^2	DRAM †† (0.5/1/2 GB) 31.5/61.5/123.1 mm^2 Flash † (1/4/8 GB) 6.3/25/50 mm^2	DRAM †† (0.5/1/2 GB) 31.5/61.5/123.1 mm^2 Flash † (8/16/32 GB) 50/100/200 mm^2
Others	Capacitors and resistors 5/10/15 Diodes 2/2/2, transistors 1/2/3 Tantalum capacitors 0/0/2, crystals 0/1/1	Capacitors and resistors 15/20/25 Diodes 2/4/6, transistors 2/4/6 Tantalum capacitors 0/0/3, crystals 1/1/2 Steel metal shield 0.5/1/2 g, cables 1/2/5 cm	Capacitors and resistors 40/50/60 Diodes 2/4/6, transistors 4/7/9 Tantalum capacitors 0/0/4, crystals 1/2/4 Steel metal shield 0.5/1/2 g , cables 1/2/5 cm	Capacitors and resistors 75/85/100 Diodes 2/6/10, transistors 7/10/15 Tantalum capacitors 0/2/4, crystals 1/2/4 Steel metal shield 0.5/1/2 g, cables 1/2/5 cm
PCB	FR4 (4 layers) 8/10/15 cm^2 Solder Paste (SAC305) 4/8/13 mg	FR4 (4 layers) 15/35/50 cm^2 Solder Paste (SAC305) 28/53/98 mg	FR4 (8 layers) 35/50/100 cm^2 Solder Paste (SAC305) 99/155/249 mg	FR4 (8 layers) 80/120/150 cm^2 Solder Paste (SAC305) 178/265/454 mg

... *(continue on the next page)* ...

Table 2.2 Continued.

Funct. Block	HSL-0	HSL-1	HSL-2	HSL-3
		Hardware Specification Level (HSL)		
	...	*(continue from previous page)*	...	
Power Supply	Mains powered Power transistor 2/3/4 Diodes power 0/1/2, radial capacitor 2/3/4 Miniature coil 2/3/4, ring core coil 0/1/1 Power cable 0.5/1/1.5 m CEE 7/4 Schuko plug 0/1/1	1 Coin cell Li-Po/2 AAA alkaline/2 AA alkaline	Li-ion battery ⋆ 10/50/100 g Power transistor 0/1/2 Diodes power 0/1/2, radial capacitor 0/1/2 Miniature coil 0/1/2	Li-ion battery ⋆ 10/50/100 g Power transistor 0/1/2 Diodes power 0/1/2, radial capacitor 0/1/2 Miniature coil 0/1/2 External IC ‡ 5/15/25 mm^2
Processing	MCU * 5/10/17 mm^2	Application processor △ 20/30/45 mm^2 Auxiliary MCU * 5/10/17 mm^2	Application processor △ 50/60/75 mm^2 Auxiliary MCU * 5/10/17 mm^2	Application processor △ 75/100/125 mm^2 Auxiliary MCU * 5/10/17 mm^2
Security	Embedded in *Processing* or non-existent	External IC ‡ 1/2/3 mm^2	N/A	N/A
Sensing	No sensor	Electret microphone 0.05/0.1/0.2 g	Single-multiple sensors ◦ 0/3/5 mm^2	Single-multiple sensors ◦ 0/3/5 mm^2 Single CMOS imager ‡ (1/4"-2/3") 8/30/58 mm^2
Transport	No transport	Transport from China to Europe Truck distance : 100/300/600 km Plane distance : 6100/6775/7400 km Total weight = 50/100/300 g	Transport from China to Europe Truck distance : 100/300/600 km Plane distance : 6100/6775/7400 km Total weight = 300/650/900 g	Transport from China to Europe Truck distance : 600/900/1200 km Plane distance : 6100/6775/7400 km Total weight = 900/1500/2000 g
User Interface	No user interface	Switch-button 0/1/2 LED 1/2/4	Switch-button 0/2/3 LED 2/4/6, LED driver ‡ 0/1/2 mm^2 Speaker 2/10/40 g, audio driver ‡ 1/2/5 mm^2	Switch-button 2/3/4 LED 3/5/8, LED driver ‡ 0/1/2 mm^2 1 LCD screen ⋄ 5/25/100 cm^2, driver ‡ 0/1/2 mm^2

◦ CMOS 0.25μm ‡ CMOS 0.13μm * CMOS 90nm ▲ CMOS 22nm △ CMOS 14 nm † Flash 45nm †† DRAM 57nm ⋆ data from [134] ⋄ data from [135]

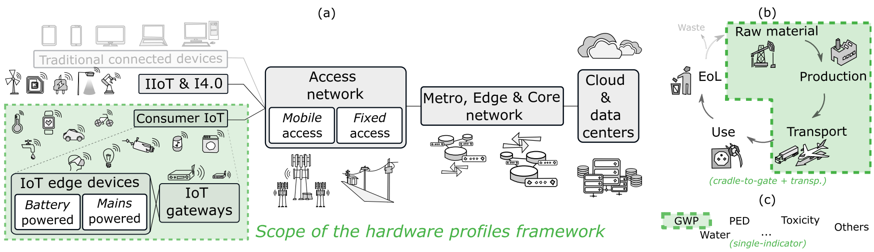

Fig. 2.2 Graphical representation of the system boundaries considered for the hardware profile framework. (a) Schematic IoT network representation, adapted from [136, 32, 132]. The framework focuses on the IoT edge devices and gateways. (b) Life-cycle phases. Use phase and end-of-life are not taken into account. (c) Impact categories and indicators. The framework focuses only on GWP, i.e., the carbon footprint.

2.2.2 Modeling assumptions

This section details the modeling assumptions used in the framework, which is built up on the LCA methodology.

- **Goal and scope:** The goal of the framework is to have a better understanding and evaluation of the carbon footprint of the production of a wide variety of IoT edge devices. Several hardware profiles are considered to illustrate the diversity of IoT edge devices and point out the variability existing between different applications and designs. It also allows a streamlined yet specific assessment for cradle-to-gate life cycle impacts of a given IoT edge device.
- **Functional unit:** The functional unit is *a single IoT edge device defined by its hardware profile*.
- **System boundaries:** The framework considers a cradle-to-gate analysis including life cycles phases and processes from raw material extraction and production. Transport to the use location is also taken into account. Only IoT edge devices are covered in the framework as depicted in Fig. 2.2. The use phase, the associated usage of networks and infrastructures and the end-of-life are not covered by this framework. Some cut-offs have been applied: board connectors, chargers, final packaging materials and final assembly[1] are not taken into account in this framework.
- **Impact categories:** The framework focuses on the carbon footprint evaluation and considers only the GWP midpoint indicator with the ReCiPe 2016 v1.1 (H) method.

[1] PCB assembly is considered.

Standards motivate the use of specific data with respect to time, geography and technology [109]. However, primary data is extremely hard to access for ICT devices and electronic components in general. Moreover, as the production of electronics components is known to be a very intensive process in terms of resources and energy [94, 19], great care should be taken when mapping hardware components to impact factors or entries in databases. When external secondary data is used for the components that are not available in Sphera LCA, it is mentioned explicitly in Table 2.2. For several components, we also provide comparison with other sources in the supplementary material, e.g., ecoinvent v3.5, Base Carbone and scientific literature. The modeling of each functional block and HSL is done within the Sphera LCA software accordingly to Table 2.2. Key details, assumptions and their limitations can be found in the Appendix A. Let us mention that no recycled material has been explicitly introduced when modeling the IoT edge devices in Sphera LCA: all materials are virgin materials. When an entry of the database is scaled in Sphera LCA, acquisition processes are scaled accordingly. Transportation within the processes is taken into account in the databases but exact details are not available in the documentation. Electricity mixes are location-based and are also taken into account in the databases.

2.3 Results

This section first presents the carbon footprint estimates of the framework, which is then applied on four specific case studies.

2.3.1 Evaluating the carbon footprint of hardware profiles

The carbon footprint evaluation of each functional block and HSL is given in Table 2.4. For each HSL, three values are provided in Table 2.4. They correspond to the results for the three set of parameters (i.e., low, typical, and up) defined in Table 2.2, which captures the presence of variability within the HSL. The results provided by the framework for a given hardware profile should hence be taken as a range of carbon footprint estimates rather than a precise value. This range of values is also represented in the different figures by errors bars.

The total minimum and maximum GWP values obtained in the framework with respect to functional blocks are respectively 0.3 kgCO_2eq and 47.41 kgCO_2eq. More details regarding the LCA modeling are provided in Appendix A and Appendix B.

Table 2.4 Carbon footprint for each functional block and HSL in the framework. Lower, typical and upper values are given in $kgCO_2eq$, according to Table 2.2. The values have been rounded to two decimal places.

Functional Block	HSL-0 low	HSL-0 typical	HSL-0 up	HSL-1 low	HSL-1 typical	HSL-1 up	HSL-2 low	HSL-2 typical	HSL-2 up	HSL-3 low	HSL-3 typical	HSL-3 up
Actuators	0.00	0.00	0.00	0.03	0.06	0.12	0.17	0.33	0.66	1.03	4.12	6.19
Casing	0.00	0.00	0.00	0.04	0.27	0.63	0.88	2.13	3.14	3.06	4.26	5.93
Connectivity	0.00	0.00	0.00	0.08	0.17	0.34	0.53	0.82	1.26	1.21	1.36	1.63
Memory	0.00	0.00	0.00	0.05	0.18	0.74	0.82	1.91	3.63	1.88	3.73	7.27
Others	0.06	0.11	0.14	0.14	0.22	0.31	0.28	0.41	0.54	0.49	0.64	0.85
PCB	0.13	0.16	0.24	0.24	0.57	0.81	1.12	1.60	3.20	2.56	3.84	4.80
Power Supply	0.18	0.52	0.66	0.02	0.18	0.38	0.25	1.36	2.71	0.37	1.72	3.32
Processing	0.08	0.17	0.29	0.66	1.05	1.60	1.58	1.94	2.52	2.31	3.13	3.98
Security	0.00	0.00	0.00	0.01	0.02	0.03	-	-	-	-	-	-
Sensing	0.00	0.00	0.00	0.01	0.02	0.04	0.00	0.03	0.04	0.19	0.77	1.47
Transport	0.00	0.00	0.00	0.18	0.40	1.35	1.07	2.62	4.05	3.34	6.30	9.34
UI	0.00	0.00	0.00	0.03	0.06	0.12	0.19	0.75	2.60	0.17	0.61	2.01

2.3.2 Applying the framework on case studies

In order to illustrate how these results can be used to estimate the carbon footprint of new custom hardware profiles, we apply the framework on several existing IoT edge devices, i.e., an occupancy sensor, a connected home assistant, a drone, and a smart watch. The selection of these case studies was mainly guided by two constraints, namely (i) the case studies must capture a diversity of hardware profiles, and (ii) online teardown reports[2] must be available if the price of the device did not allow for an in-house teardown. Figure 2.3 shows the four hardware profiles and the results for the case studies. The results are given according to the low-typical-up set of parameters defined in Table 2.2 for each functional block.

Occupancy sensor

An in-house teardown is carried out on the HUE occupancy sensor from Philips. The very low complexity of the device is reflected by its hardware profile, where the majority of functional blocks have the lowest level of HSL. The resulting cradle-to-gate carbon footprint of the occupancy sensor is evaluated at about 1.4 $kgCO_2eq$ (0.6 to 3.2 $kgCO_2eq$). Yet, a small Flash memory (4 Mb) is present on the edge device but not captured by the hardware profile. In addition, let us mention that these results are for the production of one battery, which should be adapted if a higher number of batteries is required over the total lifetime. As this IoT edge de-

[2]Teardown reports provide specific details regarding the hardware components used in a given product. If the bill of material is not directly available (which is often the case), teardown reports are useful to identify the constituting components of the product. In-house teardown can also be conducted, although this requires a physical access to the product.

vice needs a gateway to function properly, an additional hardware profile could be generated for the gateway by using the framework.

Connected home assistant
An in-house teardown is carried out on the Google Home mini, which is the light-weight version of the Google Home assistant. The hardware profile depicts increased complexity, but this remains limited to specific functional blocks such as user interface, memory, PCB, and others. The framework provides an overall streamlined carbon footprint of about 7.3 $kgCO_2eq$ (3.8 to 14.9 $kgCO_2eq$). Nonetheless, the carbon footprint evaluation of the loudspeaker should be further investigated as it weights about 80g, which is not properly captured by its hardware profile. Furthermore, the microphone of the Google Home mini is a MEMS microphone, which is not well captured in HSL-1. The silicon die area for ICs is obtained through chemical die inspection. As an example, this shows that the die size of the main SoC of the system (Synaptics AS-370) is about 25 mm^2. More details regarding the teardown are given in Appendix B. External devices used to connect to the home assistant are not taken into account.

Drone
On-line teardown reports are used for the DJI MAVIC mini. Although this is a light-weight drone of less than 250g, the hardware profile shows the higher complexity of the IoT device, mainly due to the presence of small motors, a camera, a bigger battery, and more electronic components. The framework yields about 14.1 $kgCO_2eq$ (6.1 to 23.4 $kgCO_2eq$). The propellers usually made out of glass-fiber-reinforced composite or carbon-fiber-reinforced material are not captured by the hardware profile. In addition, some ICs were impossible to identify and therefore discarded, as detailed in Appendix A. The smartphone used to acquire real-time data from the drone is not taken into account and the remote controller is not considered although a dedicated hardware profile could also be generated for it.

Smart watch
On-line teardown reports are used for Apple smart watches and the Garmin Fenix 5 smart watch. The hardware profile of the smart watch shows a higher complexity, especially in terms of memory, processing, and user interface. The resulting carbon footprint is evaluated around 10.4 $kgCO_2eq$ (5.4 to 19.5 $kgCO_2eq$). Nevertheless, several components do not have a datasheet or are impossible to identify which prevents precise inventory. For instance, this is the case for some ICs or TAPTIC engines in Apple's products, which can hence not be modeled. In addition, the casing is likely made of complex alloys which are not properly captured by the framework. Overall, the streamlined carbon footprint evaluation is hence likely to be underestimated.

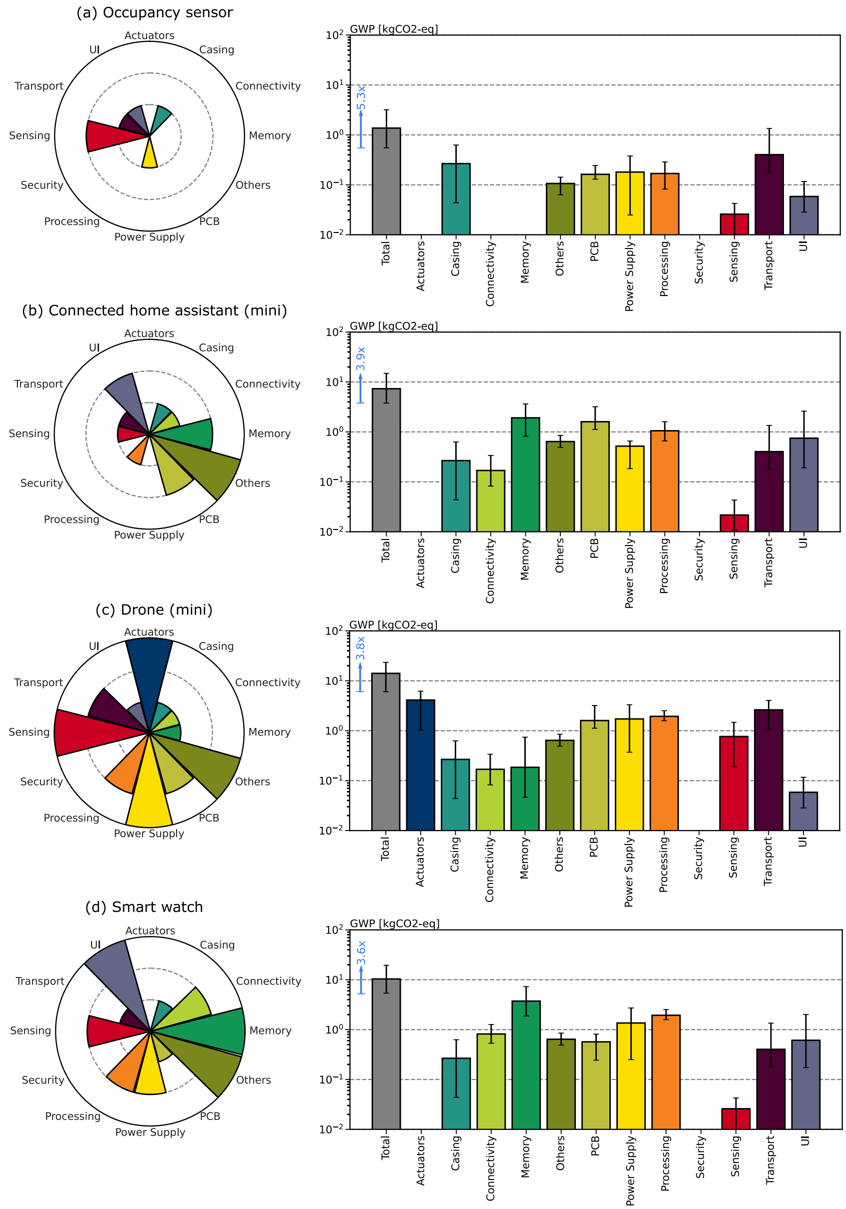

Fig. 2.3 Carbon footprint estimates based on IoT hardware profiles for the case studies considered in the framework: (a) a Philips HUE occupancy sensor, (b) a Google Home mini connected home assistant, (c) a DJI MAVIC mini light-weight drone and (d) a smart watch from Apple and Garmin.

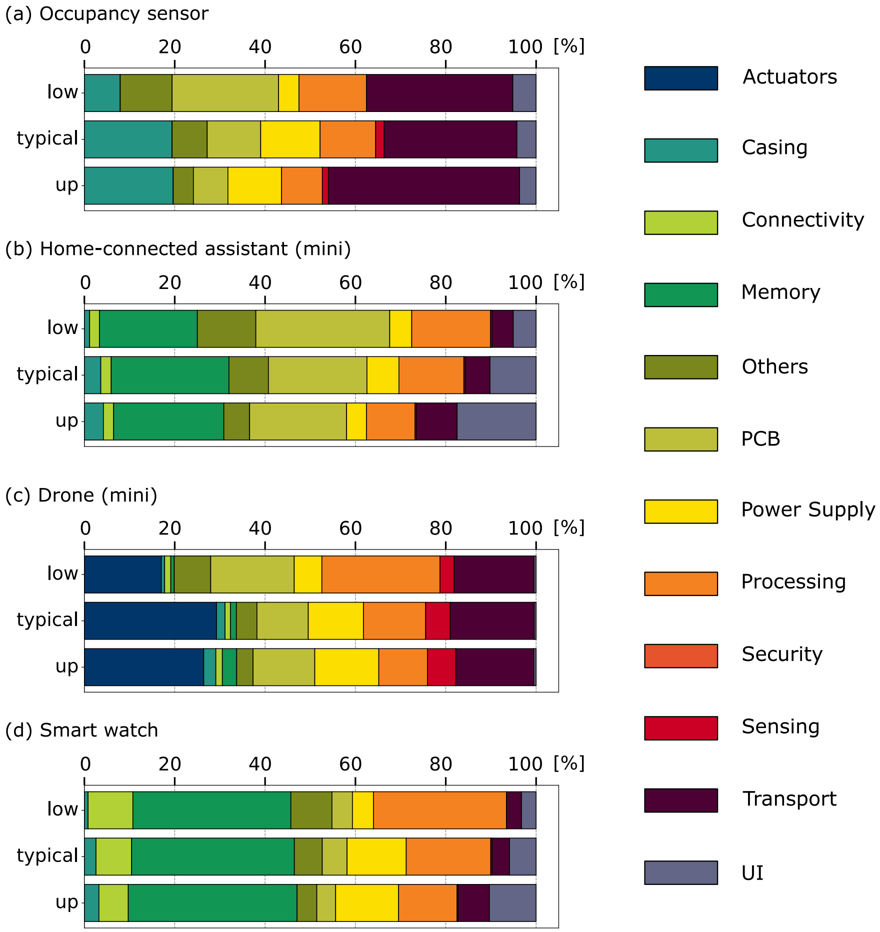

Fig. 2.4 Relative contribution of each functional block to the total carbon footprint of each case study.

2.3.3 General interpretation of the case studies results

For simple IoT edge devices with limited functionality such as the occupancy sensor, the resulting cradle-to-gate carbon footprint remains approximately below 3 $kgCO_2eq$, which is a fairly low footprint. A main part of the carbon footprint is caused by the non-electronic parts such as the casing and transport. For more complex IoT nodes such as the connected home assistant, the drone, and the smart watch, the cradle-to-gate carbon footprint is generally higher than 5 $kgCO_2eq$ and can increase close to 25 $kgCO_2eq$. In these cases, Fig. 2.4 shows that electronic components such as ICs and PCB are responsible for a significant part of the carbon footprint. As depicted by the total bars in Fig. 2.3, the ratio between the upper and lower values for each result can be up to a factor 5×. This can be further reduced for each case study by a more in-depth analysis using Table 2.2 and Table 2.4.

Actuators and casing can, in some cases, be responsible for an important share of the carbon footprint evaluation, which motivates to avoid considering only electronic components in the LCA of IoT devices. The *connectivity* functional block has a limited responsibility in terms of embodied impacts even if it is a critical feature for IoT devices. The low contribution of displays is mainly due to the small screen sizes considered. Among the four case studies, none has components specifically dedicated to security. Most of the time, these are directly integrated into components from other functional blocks, e.g., within an MCU.

2.4 Discussion

This section discusses the known limitations of the framework, conducts a brief sensitivity analysis, compares the results with other studies, and provides critical feedback on the current adoption of the framework in other studies and reports.

2.4.1 Limitations

Although the approach proposed in this chapter offers promising advantages to systematically integrate environmental considerations in the field of IoT, it embeds also a list of limitations that are discussed in this section. These limitations should be considered when using the framework.

(1) This framework is obviously less specific than a dedicated full LCA for a given device. The framework therefore provide a range of carbon footprint evaluation and not a very precise estimate.

(2) The majority of the framework is modeled with a software and a database which are not open-source. Even if the use of advanced databases allows a better modeling of the impacts, it hinders a wide uptake and the continuous improvement by the scientific community. However, even if there are few alternatives (e.g., OpenLCA, Brightway2), these remain dependent on private databases.

(3) Using the framework assumes that the user have access to (or can retrieve) specific information regarding the hardware of the IoT edge device (e.g., bill of materials, components, etc.), which is not always the case.

(4) Even though the framework already captures a wide variety of hardware profiles, blind spots remain (e.g., sensors, energy harvesting) and the trade-off between generality and specificity still exists. Nevertheless, given the very wide variety of IoT devices and the growing trend to deploy the IoT, using a consistent framework appears to be a very promising solution [18]. The definition of the HSL could be enhanced and refined by carrying out systematic teardowns over a wide variety of IoT edge devices and gateways. Indeed, we mainly used datasheets, online teardown reports, products specifications and approximations to derive the Table 2.2. For instance, inspiration for further work could be sought in a recent paper [137] which discloses a disassembly-based bill-of-material database for 95 consumer electronic products. This provides valuable data about the materials and components constituting these devices, which are very rarely disclosed as information. However, very few IoT devices are included and substantial information is lacking to perform LCA for electronics components, e.g., die area values and ICs inventory.

(5) The framework is fully based on a bottom-up approach. This offers a higher resolution than a top-down approach but inherently suffers from truncation error [18, 77] and system simplification, therefore leading to potential underestimation of the actual impacts.

(6) Finally, the framework does not cover the whole life-cycle of IoT devices and evaluates only the carbon footprint, hence only covering a small fraction of environmental impacts.

2.4.2 Sensitivity analysis

First, the stability of the results must be analyzed with respect to the modeling of the IoT edge devices. As the framework can model several combinations of functional blocks, it is important to understand where the strongest impacts are. For each HSL, uncertainty was considered through lower-typical-upper bounds. These bounds are systematically provided and clearly displayed in all results to show the variability associated with the variations of hardware specifications within a given HSL, as presented in Table 2.2. This can be seen as a local sensitivity analysis based on parameter variation, which avoids results to be point estimates. The sensitivity of the results with respect to each functional block and HSL has been analyzed as shown in Fig. 2.5. This also shows that the ratio between the maximum and minimum carbon footprints obtained in the hardware framework can reach a factor of 158×. This clearly underlines the wide range of carbon footprint estimates for IoT edge devices with different hardware profiles. To put this in perspective, the ratio between maximum and minimum carbon footprint evaluations of smartphones lies usually below a factor 10× [19]. The results provided by our framework for the case studies show that the carbon footprint estimates obtained for a given hardware profile could vary up to a factor 5×, which is still significant. Although it is clear that our framework cannot outperform the precision of a dedicated full LCA that would fully focus on one single IoT edge device, it can still provides a streamlined carbon footprint evaluation for multiple products while maintaining a high resolution on electronic components. Moreover, the framework explicitly includes uncertainty evaluations through the estimations of variations in hardware specifications. Although this is already an improvement given the lack of variability evaluation for the hardware production in current environmental assessments [27, 91] this only addresses a subset of the uncertainty sources presented in Chapter 1, as it is mainly focused on variability between objects and parameter uncertainty.

It is also important to discuss what could be the impact of internalizing limitations in the framework. Bulky casings in aluminum or steel and heavy actuators or speakers with magnets are not well covered in this framework and could increase the final footprint. This could be addressed by scaling the carbon footprint of the related functional block with the ratio of the weights. Another source of variation is the scaling of silicon die area based on the outer dimension of an IC chip package. The wide variety of packages and the variability in die-to-package ratio can lead to significant errors [18, 19, 138]. Indeed, using on-line teardown reports to make the LCA of electronic products is more difficult and less precise because assumptions have to be made rather than using measurement data. Specifically, necessary information is not available in the datasheet of components or in existing on-line public teardown reports [18, 19]. This strongly limits the possibility to carry out LCA for IoT edge devices. Regarding the results sensitivity with respect to the cut-offs that have been introduced, variation due to final assembly is expected to be up to +10% [19]. Connectors would have a limited impact with respect to GWP but gold usage contributes more to other impact categories, e.g., ecotoxicity [20, 139]. Chargers could be modeled using the power supply functional block, yet this would probably be an underestimation.

Finally, the sensitivity of the results with respect to the database that was used could be questioned. Indeed, the discrepancies between the existing databases could impact the results. In the framework, we made an extensive use of the Sphera LCA Extension XI (Electronics) database for its advanced modeling and level of details for electronic components. However, some critical parts are not modeled in Sphera LCA databases, such as WiFi modules, power management ICs, CMOS cameras, sensors, Li-ion batteries and displays. In general, this is a concern for IoT edge devices which are intended to bring these different components together. Regarding ICs, variation in the emission factor per die area is introduced[3] in [19, 133].

[3] A deeper analysis of the emission factors for different technology nodes will be provided in the next chapter.

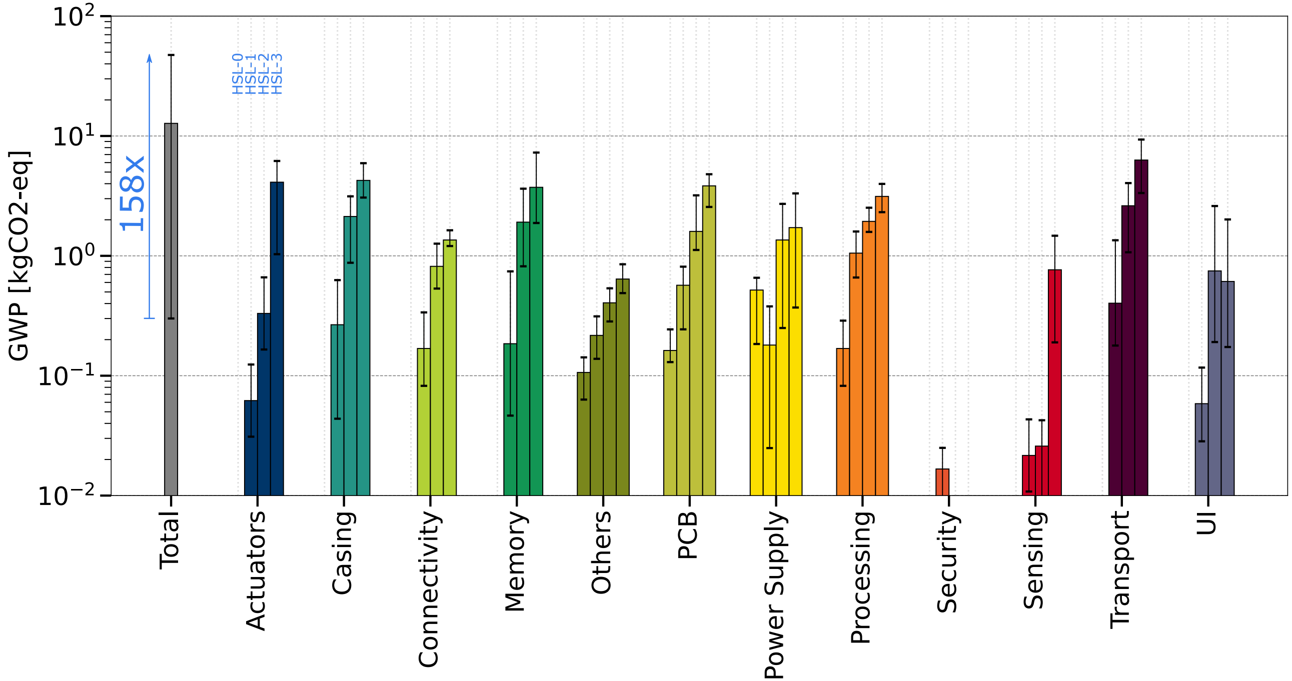

Fig. 2.5 Sensitivity analysis across functional blocks and HSL. This shows the need to account for the heterogeneity in IoT edge devices as the production carbon footprint of simple and complex devices can be spread by a factor of 158×, as modeled by our framework.

2.4.3 Comparison with other studies

Very few LCA results of IoT devices are available for comparison and benchmarking purposes. The carbon footprints of several sensors (e.g., motion and temperature-humidity sensors) are given in Bates [118] but the study from 2013 is likely outdated and very few details are available.

Google [140] and Apple [141] have published the carbon footprint of some of their products, including connected assistants and smart watches. Figure 2.6 shows the comparison between the results of our framework and the aforementioned studies. It provides very similar trend and accounts for the variation between devices but the absolute results given in Google and Apple's environmental reports are usually higher than those predicted by this framework, up to a factor 3× for production and 2× for transport. A similar comparison with Apple's LCA results was done in [101] for conventional connected devices (e.g., laptops, netbook, tablets and music player) and an undershoot factor ranging from 1.3× up to 2.7× was also observed. The author if that study pointed out truncation error as the main reason to explain the undershoot [18, 77]. Indeed, some internal specific processes are obviously unknown and consequently omitted here. The use of a different impact database by Apple could also partially explain the undershoot as the values for the IC carbon footprint in the Sphera LCA databases are lower than the literature [18, 19, 20] (see next chapter). However, the lack of details and transparency in their reports makes the comparison difficult, as also mentioned in [18]. The more complex modeling of casing materials with an important share of metal and the presence of magnets[4] in actuators seem to have a significant impact on carbon footprint evaluation. They were also identified as possible reasons to explain the undershoot. Regarding transportation, it is likely that more intermediate steps and travel methods occur in the logistics, thus impacting the distances and the associated footprint. If transportation packaging materials are considered, the total weight increases which also increases the carbon footprint evaluation.

[4]Depending on the type of magnets, rare earth elements may be used to improve their magnetic properties, which would likely increase the environmental impacts associated with the production of the magnets.

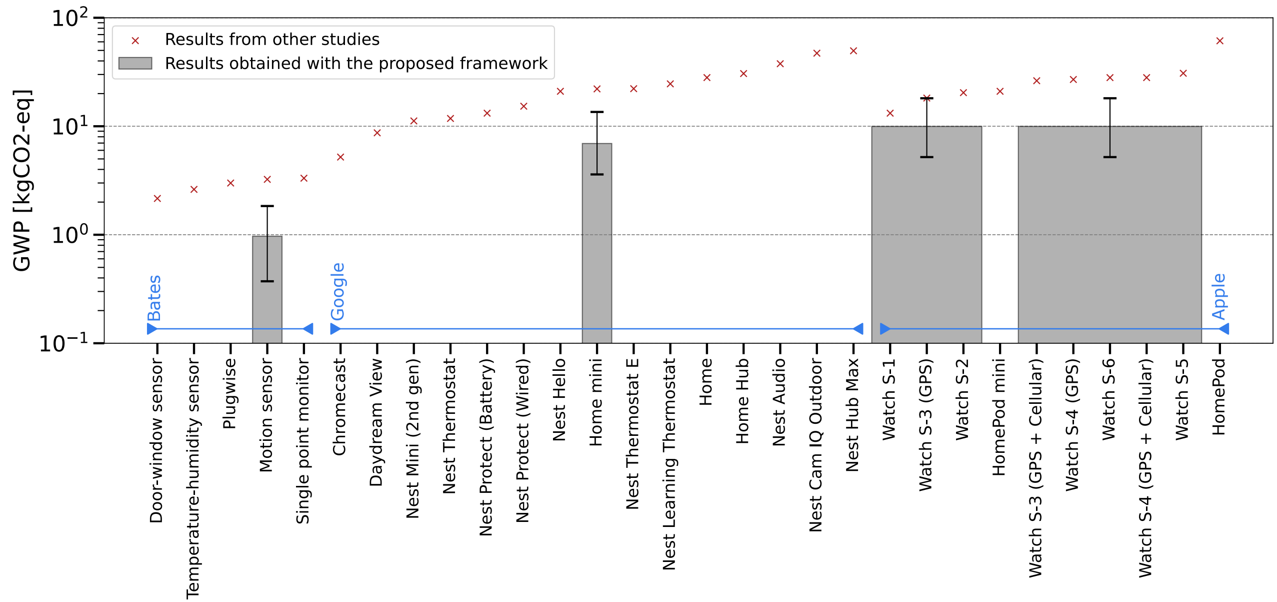

Fig. 2.6 Comparison between the carbon footprint estimates obtained for the case studies in this work and independent reports or studies when available, i.e., occupancy sensor [118], connected home assistant [140], and smart watch [141]. Only production is shown for clarity. No benchmark data were found for the drone.

2.4.4 Critical opinion on the uptake of the framework in the literature

Since its publication in mid-2021, several recent works have used the hardware profiles framework to streamline the carbon footprint evaluation of IoT devices. This section hence briefly discusses the benefits and drawbacks associated with the effective uptake of the framework.

The major benefit of the proposed framework is that it seems to effectively support the systematic evaluation of the carbon footprint of IoT devices in other studies. For instance, [142, 143] used the framework to streamline the carbon footprint evaluation of the production for their IoT solution and IoT network analyses. Alvarado et al. [142] further explored eco-design questions at the scale of an IoT network while also considering the embodied carbon footprint of the IoT nodes, similarly to [144]. Another study [145] proposed an online version of the framework, extended with use-phase and end-of-life estimates for low-power microcontroller systems. Outside of the academia, the study commissioned by the European Parliamentary group of the GREENS/EFA [146, 147] reused the framework and extended it to multi-indicators, together with modeling the end-of-life. This was done based on the EIME [148] and ecosystem [149] databases[5]. Similarly, the report from ADEME/ARCEP published early 2023 includes a section on the footprint of IoT devices, which reused the hardware profiles framework together with the report from the IEA [31] to estimate the footprint of IoT devices in France. The report targets a broader scope as it evaluates the environmental footprint of ICT in France from 2030 to 2050 [66]. The framework has also been used by Boavizta [150] and by the French company called Mavana [151] as a basis for evaluating the carbon footprint of IIoT devices. Yet, in a recent article from May 2023 [152], they explain that they had to extend the framework as the HSL defined in Table 2.2 tend to underestimate the actual hardware needed in the context of IIoT. This was anticipated and clearly mentioned in the limits of our framework. Nevertheless, they confirmed the relevancy of using a framework based on hardware profiles to streamline the carbon footprint evaluation of the IIoT devices. The framework was also used to challenge the results of a full LCA [153]. This is an interesting use of the framework, as it can provide a comparison for full LCAs. Indeed, this was not possible before because the literature on LCA for IoT devices is scarce. In the long term, this can likely improve the understanding of specific and streamlined results, and support the use of hardware profiles for streamlined evaluation. In fact, this could be used as an evolving dictionary of hardware profiles to be maintained over time. Finally, when the framework is not used for a quantitative assessment, it supports the integration of environmental considerations for IoT [154, 45, 155, 156].

[5] Information obtained directly from one of the author.

Unfortunately, the adoption of the framework comes also with several pitfalls. First, the variability of the framework with the lower and higher bounds and the estimate regarding the truncation error is usually not reported. Even if it complicates the analysis and interpretation of the conclusions, this should be done systematically. In fact, uncertainty is inherent to LCA and it must be reported as often as possible, especially for embodied impacts [27]. Then, some studies are misusing the conclusions of the study by stating claims on the impacts of the use phase or the ICT infrastructure [157], although this is not even covered in the framework. Finally, it is important to remind that the framework is not intended to replace a full LCA. It is clear that the framework reduces the need for a detailed modeling and for LCA expertise, which therefore significantly speeds up the environmental assessment. Yet, it comes together with simplifications and potential omissions, which should not be forgotten when using the proposed framework.

2.5 Summary

To take a step towards the systematic consideration of the environmental impacts generated by IoT edge devices, this chapter proposes a quantitative framework to evaluate the carbon footprint due to the production and transport of such devices. The framework is based on state-of-the-art existing tools and databases and it also helps to cope with the wide variety of IoT devices by introducing the concept of hardware profiles. In fact, we showed that the carbon footprint evaluation of IoT edge devices with different hardware profiles can vary by a factor greater than 150×. This clearly highlights the need to consider the heterogeneous nature of IoT devices. Furthermore, we applied the framework on four IoT case studies and we demonstrated that it can be used to streamline the carbon footprint evaluation of a variety of IoT devices. Most importantly, we proposed the concept of *hardware profiles* to capture the heterogeneity of IoT devices in streamlined assessments, while preserving hardware specificity up to a certain level. Nevertheless, it is clear that further work is needed to (i) better evaluate the variability introduced by key components such as ICs, (ii) take into account the remaining phases of the life cycle, (iii) include the associated use of networks and infrastructures, and (iv) to take more environmental indicators into consideration. The next chapter focuses on (i) while Chapter 4 targets the points (ii) to (iv).

3

Digging the environmental footprint of integrated circuits through literature review and meta-analysis

We cannot solve our problems with the same thinking we used when we created them.
– Albert Einstein

INTEGRATED circuits are key building blocks of ICT equipment, hence supporting digital products and services. However, it is widely acknowledged that even though the size of ICs is usually very small, their production is very intensive in terms of raw materials, chemicals, water, and energy due to the complex processes involved [94, 158]. It is therefore not surprising that the production of ICs is responsible for an important share of cradle-to-gate impacts of existing ICT devices [19, 20, 100, 110, 159, 160, 161]. This observation is further supported by the results presented in Chapter 2 for a range of IoT devices. Moreover, important variations can be observed in LCA results due to the presence of ICs, even for similar devices. This is illustrated in Fig. 3.1 in the case of smartphones [19]. In practice, it can be very difficult for LCA practitioners to chose between the different data sources to model the environmental footprint of ICs, and even more difficult to

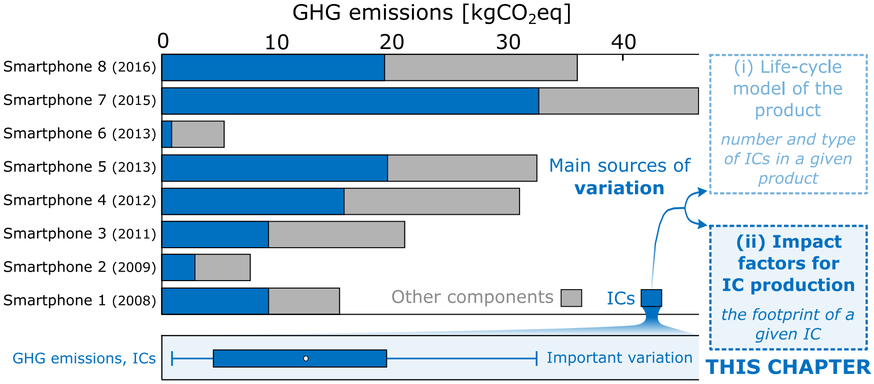

Fig. 3.1 Example of the important variation regarding the embodied carbon footprint evaluation of ICs in existing LCA of smartphones, data from [19]. This chapter focuses on the variation of impact factors for IC production.

understand to what extent this choice impacts the LCA results. Consequently, special attention must be given to the evaluation of the environmental footprint of IC production. Indeed, an important bottleneck is the lack of a clear and comprehensive understanding of the different estimates existing to assess the environmental footprint of ICs. Indeed, the comparison between studies is hard and the lack of transparency prevents efficient uptake of the results [19].

To overcome this problem, the second step of this thesis digs the evaluation of the environmental footprint of IC production by proposing the first systematic and extensive analysis of the data available, while going well beyond existing scientific literature.

This chapter is structured as follows. First, Section 3.1 provides a brief overview of the state of the art and supports the need for a better understanding of the environmental impacts of IC production. Then, Section 3.2 details the methodology used for the literature review. Next, we leverage this literature review in Section 3.3 to perform an analysis on both qualitative and quantitative aspects with the identified sources. We consider three environmental indicators, i.e., energy consumption, carbon footprint and water consumption. Finally, Section 3.4 discusses known limitations and compares the results with other studies.

3.1 Context

To support the evaluation of environmental impacts of IC production while going beyond the sole consideration of the carbon footprint, LCA is generally used. However, important practical obstacles are known in the literature, as detailed in the rest of this section.

3.1.1 Related Works

LCA has been carried out for semiconductors for the last decades and several pioneer works have assessed the impacts of specific IC electronic components [94, 95, 98, 111, 104, 161, 162, 163] and ICT devices [18, 19, 20, 71, 77, 164, 165]. Unfortunately, the impacts related to the production phase are usually out of reach for people outside of semiconductor foundries [19, 111, 161]. This strong limitation partially explains the important lack of up-to-date data used to model the environmental impacts of semiconductors, which is reinforced by confidentiality barriers due to intellectual properties [111], the increasing complexity of advanced technologies [95, 97, 111], and the rapid innovation cycles in the nanoelectronics sector [104, 110] as captured by the emblematic Moore's law [166, 167]. These fundamental limitations have been known for years in the field of LCA for semiconductors [18, 19, 94, 110, 111, 168] and can introduce significant variations in the LCA of ICT devices [19, 110], as depicted in Fig. 3.1. However, the comparison of LCA results from different studies is generally very complicated and time-consuming, mainly because of the lack of transparency in modeling assumptions and source data [18]. Without a better understanding of the gaps and similarities between existing studies on the environmental footprint of ICs, it is difficult for LCA practitioners that us them as input data to come up with understandable results.

3.1.2 Objectives

This chapters hence aims at improving the current knowledge regarding the environmental impacts of IC production. The objectives are threefold. First, it is critical to identify currently available LCA data for IC production, which requires the preliminary identification of key sources on this topic. To the best of our knowledge, this has never been done before and prevents a proper overview of current models available for the evaluation of IC environmental footprint. Then, given the fact that scope mismatch between different studies is a well-known issue in the LCA community, the second objective is to identify the scope mismatch for the selected studies, in a systematic way. Finally, building on the two previous objectives, it is needed to evaluate the variation existing in LCA data for IC production, as this can significantly impact LCA results of IoT and ICT products or services.

3.2 Methodology

This section starts by providing details about the systematic literature review carried out to identify key sources from four literature categories. Then, the methodology used for the qualitative and quantitative analysis is presented. More specifically, we detail the choice of environmental indicators under study, the motivation for a normalization by silicon area, and we define ten objective features specific to IC production to characterize the scope of the studies included in the review.

3.2.1 Literature review

The PRISMA methodology [169] is used to identify, sort, and report the relevant sources, as shown in Fig. 3.2. For the identification phase, two databases are searched (IEEE Xplore and Google Scholar), backed-up by cross-referencing and the authors' previous knowledge in the field of LCA for semiconductors. The following keywords are used: semiconductor, life cycle assessment, footprint, environmental impacts, production, integrated circuits, logic, memory, electronics, CMOS and manufacturing. This allows the identification of 95 scientific studies and 59 non-scientific reports, for which titles and abstracts are then screened to exclude those that are not relevant for the research question. The selection is then performed by the author based on exclusion criteria, as further detailed in Fig. 3.2. For instance, we include only studies disclosing quantitative values of environmental footprint related to ICs production, and studies published after 2010. In order to cover a wide range of data while avoiding field-related biases, we consider four different literature categories, i.e., foundry reports, semiconductor industry roadmaps, scientific literature, and commercial state-of-the-art LCA databases. More details are given below for each literature category.

Foundries have to annually report their environmental performance in corporate sustainability responsibility (CSR) reports which ensure a systematic source of information. Nevertheless, the value chain involved in the creation of an IC gathers a wide range of actors such as integrated device manufacturers (IDMs), fabless firms, and pure-play foundries [170], while assembly and testing are often outsourced. We focus on CSR reports of pure-play foundries as they only manufacture ICs, without having any in-house design capabilities or side-activity that could interfere with the reported data. Four pure-play foundries are considered in this study, i.e., Taiwan Semiconductor Manufacturing Company (TSMC), United

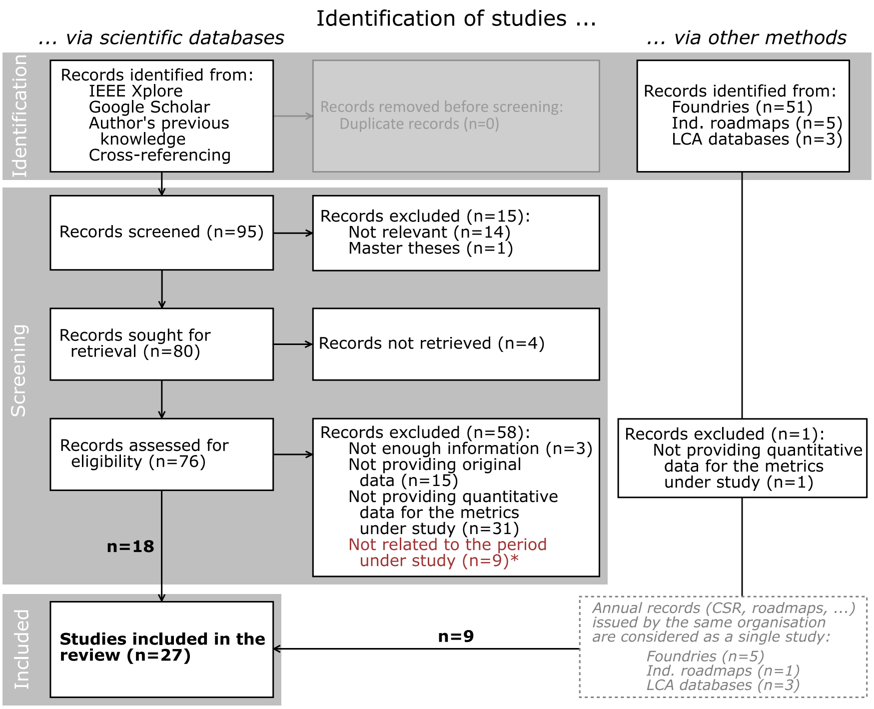

Fig. 3.2 Identification of relevant studies for the systematic review of the literature on the environmental footprint of IC production. Screening and sorting of studies are based on exclusion criteria specified in the chart. The final list of studies included in the review is provided in Table 3.3.

Microelectronics Corporation (UMC), Semiconductor Manufacturing International Corporation (SMIC), and GlobalFoundries (GF). We also include the IDM STMicroelectronics (STMicro) because they provide data in their CSR reports that can be directly related to their own production unit and IC fabrication capacity. For the sake of readability, annual records issued by the same organization are considered as a single study, i.e., ten CSR reports over ten years turns to $n = 1$.

Roadmaps provide targets rather than actual data from on-site measurements [97, 98, 171]. The most iconic example is the International Technology Roadmap for Semiconductors (ITRS), renamed International Roadmap for Devices and Systems (IRDS) in 2016. These roadmaps are published by a group of industry experts from Europe, Japan, Taiwan, the United States of America and Korea. They include a specific chapter on environment, safety and health (ESH). Even if roadmaps are published on a yearly-basis, only the 2015 edition is included for further analysis as it is the latest version providing quantitative data for the metrics under study. Apart from the ITRS roadmaps, we found no other roadmap disclosing quantitative environmental targets.

Scientific literature is an important source of data as several peer-reviewed studies have been carried out over the last 20 years. Yet, due to the nature of scientific publication, it does not benefit from regular updates. Let us mention that we also included three relevant non peer-reviewed studies [139, 172, 173] in this category. As visible in Fig. 3.2, the two main reasons for the exclusion of studies are the absence of quantitative data for the metrics under study (33%) or the absence of original data (16%). In total, 18 studies (19%) are included for further analysis.

Databases from LCA tools provide specific data and usually benefit from regular updates. Three commercial state-of-the-art LCA databases are considered in this study because they are widely used among all the tools and databases available for semiconductors [19, 174], i.e., Sphera LCA [175], EIME database from Bureau Veritas [148], and ecoinvent [176].

3.2.2 Environmental indicators

Among these four literature categories, we include only sources providing quantitative data for at least one of the three following environmental indicators: energy consumption, global warming potential, and water consumption (Water). Even though these indicators do not provide a comprehensive picture of all environmental impacts [110], they already cover important aspects of the ecological footprint. In addition, they are the ones usually reported in the different literature categories [18], which makes the analysis possible.

Regarding the energy consumption, **primary energy demand** (PED) is used rather than final energy consumption for two key reasons. First, primary energy expressed in MJ is a well-known indicator used by the LCA community. Second, it accounts for the conversion and transmission efficiency of energy generation [177], which would not be possible if considering only final energy consumption. A primary energy factor[1] (PEF) of 2.5 was considered for the analysis for the sources that only have final energy data available.

Global warming potential is considered due to its effects on climate change.

[1]The primary energy (or accumulated energy) is defined as "[...] the energy that has not yet undergone any anthropogenic conversion" [178]. The relation between primary energy E_p and final energy E_f is given by $E_p = \frac{1}{\eta} E_f$, where η is the conversion and transmission efficiency, and $\frac{1}{\eta}$ is the PEF.

In order to standardize the reporting of the carbon footprint evaluation in organizations, the GHG Protocol [179] distinguishes three scopes of emissions. Scope 1 includes all the GHG emissions generated directly by sources owned or controlled by the organization[2]. Scope 2 includes indirect GHG emissions related with the generation of purchased electricity (outside of the site). Finally, scope 3 gathers the remaining indirect emissions associated with the activity of the organization, e.g., upstream and downstream emissions [179, 180].

Regarding **water consumption**, different types of water are used in the semiconductor manufacturing processes, ranging from water for cooling purposes to ultra-pure water for cleaning wafers between the different process steps, as a very low level of contaminants must be reached [163]. However, it is not always possible to distinguish between water and ultra-pure water (UPW), although water is generally purified into UPW on-site [97]. In general, very few details are given regarding the nature of the water, i.e., intake, recycled, reclaimed or reused. In the absence of more reliable information, water consumption is assumed to be the sum of total intake water and recycled water to express the total need of water for the IC production, expressed in liters (L).

3.2.3 Normalization by area

Choosing the most appropriate functional unit and metrics to characterize the environmental impacts of IC production still remains an open question, especially because semiconductor manufacturing is a fast-evolving sector [94, 158]. In this study, we decided to normalize all environmental indicators by the silicon die area in cm^2, as done in [94] and [95]. This is also supported by the presence of area in roadmaps and in the well-known power-performance-area-cost (PPAC) metrics in CMOS process development and optimization [95, 171]. Finally, the normalization per area has also an additional advantage: the total area of wafers produced over one year by a foundry is easier to obtain than the total weight or total number of transistors. This facilitates the inclusion of foundries and the consideration of macroscopic IC production volumes.

Yet, the normalization could also be done per wafer, or with respect to the number of transistors or even with respect to the weight of the IC [18, 19, 98, 164, 172]. Nonetheless, Deng and Williams [158] showed that even if normalizing per functionality (i.e., per transistor) versus typical product (i.e., per typical IC) yields different results, environmental assessments of electronics products may be more temporally robust when referring to a typical product than the rapid progress in the

[2] This terminology of emission scopes is specific to the GHG protocol in the context of carbon footprint evaluation. Although it is not part of the LCA terminology, these terms are sometimes borrowed in the context of LCA (with the same meaning).

industry would lead one to think [158]. This therefore supports a normalization by typical product (e.g., a microprocessor, an image sensor, or a DRAM memory) rather than by functionality (per transistor), which seems further supported by the analysis in [138]. Regarding the normalization by weight, it is commonly accepted that it is less relevant for IC footprint, mainly because of the very low share of the die weight compared to the package [98].

3.2.4 Defining ten objective features for characterizing the scope of IC production LCAs

Even if all the studies' results are brought back to a common functional unit, another important challenge remains: the concordance of scopes between sources. Indeed, this is a well-known concern for LCA practitioners, which is further exacerbated as several categories of sources are considered in this analysis. The mismatch in scopes can introduce variations in the results and complicates the comparison [19]. Consequently, a transparent methodology is critical to compare all sources and ensure reliable conclusions in the identification of gaps and similarities. Unfortunately, such a methodology does not exist so far. Therefore, we propose to define ten features for characterizing the scope of IC production LCAs, as presented in Table 3.1. These features are then used for the qualitative analysis.

Table 3.1 Defining ten objective features for characterizing the scope of IC production LCAs.

Feature	Description
(1) Technology type	The IC production gathers several technology types, i.e., logic, memory (e.g., DRAM and Flash), MEMS, analog, or radio-frequency. As this refers to different process flows, it can lead to different environmental impacts [20]. In addition, the distinction between front-end (FE) and back-end (BE) is important as these correspond to two distinct parts of the manufacturing process, most often carried out by different manufacturers [97]. FE combines front-end-of-line (FEOL) and back-end-of-line (BEOL) which are related to wafer processing, patterning, interconnect wires and vias whereas BE is mostly about wafer dicing, packaging, and assembly.
(2) Technology node	Semiconductor manufacturing is constantly evolving towards more advanced nodes, as illustrated by Moore's Law [171]. Identifying the technology node for a given IC is important as the manufacturing process flows are node-specific.
(3) Wafer size	Silicon wafers are the physical substrate used for ICs manufacturing. They are sawed into several individual slices from a single mono-crystal silicon ingot. Nowadays, 300 mm wafer is the standard in most foundries. As the use of wafer with larger diameters generally helps reducing edge losses [168, 171], it is important to report the wafer size.
(4) Production yield	Due to defaults and issues in the manufacturing processes, losses occur in the production lines [94]. For instance, all wafers do not end up as functional wafers, as quantified by the line yield. Similarly, the wafer yield[3] models the fact that all dies on a wafer are not good dies. It might be considered constant, or die-size dependent as in the Murphy's yield model [181]. Unfortunately, the overall production yield is a very sensitive information for manufacturers, hence rarely disclosed even though it can significantly impact the environmental indicators under study (in a nonlinear way) [168, 94]. Overlooking production yield leads to an underestimation of the environmental indicators. Moreover, yields evolve with the maturity of the process, i.e., low yields are reached at the beginning of the industrialization process but then increase over time until they reach a maturity production yield [94, 171].
(5) Infrastructure and upstream materials	Beside the environmental impacts generated by the use of the equipment needed for IC production, the overhead associated with the fab infrastructure facility and the maintenance can be significant, up to 40 to 60% [94, 168]. In addition, the production of upstream materials such as wafers and chemicals required by the process flows contributes to environmental impacts [182, 77]. It is therefore crucial to know whether both overheads are included.

... *(continue on the next page)* ...

[3] Also called the die yield.

Table 3.1 Continued.

Feature	Description
	... *(continue from previous page)* ...
(6) Geographical location	The electricity mix depends on the location of the manufacturing site, hence impacting the GWP indicator. The PEF also depends on the geographical location but is considered constant in this study.
(7) Covered environmental indicators	All sources do not systematically provide values for several environmental indicators or for all indicators considered in this study. As a multi-indicator approach is usually preferred, it is useful to detail the list of covered environmental indicators.
(8) Process details and transparent normalization	The distinction between the sources that disclose process details and the others should be carried out, as a higher level transparency fosters a deeper analysis. Life cycle inventory (LCI) is intended to foster a high level of detail but they are not always disclosed. Similarly, providing results normalized by the area is not a mandatory standard and hence not done systematically in the studies. As hypotheses are needed when normalizing the raw values, this must be clearly reported.
(9) Assessment approach	The three most common assessment approaches to carry out an LCA are the bottom-up, the top-down, and the hybrid one. The bottom-up approach has the advantage of being precise, but it is more time-consuming and suffers from truncation errors [183], resulting in a potential underestimation of the environmental impacts. The top-down approach rather uses macroscopic data and economic input-output (EIO) analysis, which eludes truncation errors but leads to a "black-box" effect, as underlying processes are unknown. The hybrid approach combines bottom-up and top-down approaches but requires more data. More details are provided in Section 1.3.
(10) Primary data and dependencies	Primary data refers to data measured directly on-site, in opposition to secondary data. The use of primary data is recommended by ETSI/ITU standards for LCA of ICT products and services [72, 109] which aim at fostering comparability across compliant studies. However, as it is very difficult to have access to on-site measurements in practice, primary data are often replaced by secondary data and very few studies can thus claim full compliance. Yet, when a source uses data and/or assumptions from another source, this creates what we call here a dependency from one source to another. This must be identified as it can introduce biases and propagation of outdated data.

3.3 Results

This section presents and interprets the results of the qualitative and quantitative analyses. First, we highlight the important scope mismatch between sources and then, we show the effect of technology downscaling on the environmental impacts of IC production.

3.3.1 Revealing the scope mismatch through qualitative analysis

Table 3.3 shows the classification of all data sources with respect to the ten proposed features. This qualitative analysis clearly shows the mismatch existing between the considered sources, revealing the complexity of properly harmonizing them. Indeed, mismatch exists among both the scopes and the LCA approaches. Due to the general lack of information across the ten features in the majority of studies, we decided not to perform such an harmonization between the sources to avoid introducing an additional variation. Indeed, several assumptions were already needed to get all sources back to the same functional unit. All these assumptions are provided in Appendix C.

Table 3.3 highlights that the data from the foundry reports are macroscopic values obtained with a top-down approach. This high level of aggregation is reflected in several features that are not differentiated despite their heterogeneity, e.g., technology type, technology node, wafer size and energy mix localization. For instance, the annual share of technology nodes in the production volumes is rarely disclosed by foundries. Moreover, it is not clear if yields are included, suggesting that values should be considered as a lower bound. Finally, for the majority of sources in Table 3.3, the scope is usually limited to the FE as it concentrates most of the activities and the highest number of process steps, at least for conventional nodes. The industry roadmaps indicate environmental targets per cm^2 of wafer out, suggesting that total yields are not included [184] nor BE environmental impacts.

Regarding the scientific literature, Table 3.3 shows that most studies are based on secondary data. The limited access to foundries compels authors to use data from databases or from already published works. This significantly increases dependencies and potential biases, which is an important limitation as it prevents an up-to-date picture of the actual environmental impacts. Dependencies identification reveals that the pioneering work of Boyd [94] has a strong influence on the rest of the literature. Although this work is of high interest, it also depends on data from Krishnan *et al.* [104], which is most likely no longer representative of current environmental impacts. In general, scientific literature is more transparent than other types of sources due to peer-reviewing and scientific approach, fostering in-depth details for the results and methodology. Scientific literature is also more prone to widen the scope of study. For instance, efforts were done to include the BE steps [20, 172, 184] which are estimated to contribute from 25 to 37% of the total energy consumption [184].

LCA databases combine interesting features from the other source types, e.g., transparency, specific technology nodes and a range of environmental indicators. Even though they are based on both primary and secondary data, they usually document their data.

Across all the sources considered in this study, upstream materials are most often overlooked even though scientific literature highlighted their strong contribution in the final results [94]. Similarly, process details are usually scarcely detailed or simply not provided. This is undoubtedly related to aforementioned limitations, i.e., the great complexity of the semiconductor manufacturing processes and the data privacy concerns. If we focus on the technology node feature, the qualitative analysis suggests two data clusters. On one side, the scientific literature and LCA databases allow for a node-wise analysis while on the other side, foundry reports and industry roadmaps provides node-aggregated temporal trends. These two clusters cannot be directly compared to each other, but they both bring useful insights to better understand the environmental impacts of IC production from different yet complementary perspectives, as explained in the following sections.

Table 3.3 Streamlined classification of all data sources considered in this study, according to the ten features defined in Table 3.1.

Features	(1)			(2)	(3)	(4)	(5)		(6)	(7)	(8)		(9)	(10)	
	Tech. type	*Front-end*	*Back-end*	**Tech. node (nm)**	**Wafer size (mm)**	**Yield**	**Infra.**	**Upstr. materials**	**Geogr. location**	**Indic. coverage**	**Process details**	**Transp. norm.**	**Assess. approach**	**Prim. data**	**Depend-encies**
Foundry reports (N=5)															
TSMC, CSR & 20-F (2010-2020)	mix	✓	✗	mix	mix	⊖	✓	✗†	GLO	⇔	✗	✗	↓	✓	✗
UMC, CSR & 20-F (2011-2020)	mix	✓	✗	mix	mix	⊖	✓	✗†	GLO	⇔	✗	✗	↓	✓	✗
SMIC, CSR (2011-2020)	mix	✓	✗	mix	mix	⊖	✓	✗†	GLO	⇔	✗	✗	↓	✓	✗
STmicro, CSR & 20-F (2011-2020)	mix	✓	✗	mix	mix	⊖	✓	✗†	GLO	⇔	✗	✗	↓	✓	✗
GF, CSR & F-1 (2011-2020)	mix	✓	✗	mix	mix	⊖	✓	✗†	GLO	⇔	✗	✗	↓	✓	✗
Industry roadmap (N=1)															
ITRS ESH (2015) [185]	⊖	✓	✗†	⊖	200;300	✗	✓	✗	⊖	PED;W	✗	✓	⊖	⊖	✗†
Scientific literature (N=18)															
Bol, ISSST (2011)[126]	L:M	✓	✗	130;45;32	⊖	✓	✓	✓	⊖	PED	✗	✓†	⇅	✗	✓
Boyd, Ph.D. (2012) [94]	L;M	✓	✗†	350→32	200;300	✓	✓	✓	USA	⇔	✓	✓†	⇅	✓	✓
Schimdt, Int J LCA (2012) [186]	L;M	✓	✗	⊖	300	✓	✓	✗	GLO	GWP	✓	✓	⇅	✗	✓
Bol, ISSSC (2012)[187]	L	✓	✓†	130;65	300	⊖	⊖	✗†	⊖	PED	✗	✓†	↑	✗	✓
Prakash, ProBas report* (2013) [184]	M	✓	✓	45	300	✓	✗	✗	⊖	PED;W	✓	✓	⊖	✗	✓
Bol, FTFC (2013)[46]	L	✓	✓†	130;65	⊖	⊖	⊖	✗†	⊖	GWP	✗	✗	↑	✗	✓
Jones, ICCAD (2013) [100]	mix	✓†	⊖	350→45	⊖	⊖	⊖	⊖	⊖	PED;GWP	✗	✓	↓	✗	✓
Wang* (2014) [173]	L	✓	✓	⊖	300	✓	✓†	✗†	⊖	PED◇	✓	✓†	↑	✗	✓
Teehan, Ph.D. (2014) [18]	⊖	✓†	✗	⊖	⊖	⊖	⊖	✓	⊖	GWP;PED	✗	✗	⇅	✗	✓
Andrae, Challenges (2014) [188]	mix	✓	✗	⊖	⊖	⊖	⊖	⊖	⊖	GWP	✗	✓†	⊖	✗	✓
Andrae, IEEE (2015) [189]	mix	✓	✗	⊖	⊖	⊖	⊖	⊖	GLO	GWP	✗	✓†	⊖	✗	✓

... (continue on the next page) ...

Table 3.3 Continued.

Features	(1)			(2)	(3)	(4)	(5)		(6)	(7)	(8)		(9)	(10)	
	Tech. type	*Front-end*	*Back-end*	**Tech. node (nm)**	**Wafer size (mm)**	**Yield**	**Infra.**	**Upstr. materials**	**Geogr. location**	**Indic. coverage**	**Process details**	**Transp. norm.**	**Assess. approach**	**Prim. data**	**Depend-encies**
				…	*(continue from previous page)*			…							
Proske, FF2 report⋆ (2016) [172]	L;M	✓	✓	32	300	✓	⊖	✗†	CN	GWP	✓	✓	⇅†	✗	✓
Ercan, ICT4S (2016) [20]	L;M	✓	✓	⊖	⊖	✓	✓	✓	⊖	GWP;PED	✗	✓	⊖	✓	✗†
Andrae, Challenges (2017) [164]	L	✓†	⊖	⊖	⊖	⊖	⊖	⊖	GLO	GWP	✗	✓	↑†	✗	✓
Kline, IGSC (2017) [161]	L;M	✓†	✗†	350→45	200	✓†	⊖	⊖	⊖	GWP;PED	✗	✓	↑†	✗	✓
Bardon, IEDM (2020) [95]	L	✓	✗	28→3	300	✗†	✓	✗†	GLO	⇔	✗	✓	↑	✓	✓
Proske, FF3 report⋆ (2020) [139]	L;M	✓	✗†	60;45;32	300	✓†	✓	✗†	CN	GWP	✓	✓	⇅†	✗	✓
Das, SEGAN (2020) [133]	M	✓†	⊖	250;130;57;45	⊖	⊖	⊖	⊖	⊖	PED	✗	✓	⊖	⊖	✓
Commercial LCA databases (N=3)															
Ecoinvent v3.5 (2018) [176]	L	✓	✓	⊖	200	✓	✓	✗	GLO	⇔	✓	✗	⇅	✗	✓
EIME, Bureau Veritas (2019) [148]	mix	✓	✗	130→7	300	✗	✗	✓	TWN	⇔	✗	✓‡	↑	✓	✓
GaBi, Sphera (2022) [175]	L;M	✓	✗◃	350→14	300	✓	✓	✓	GLO	⇔	✗	✓‡	⇅	✓	✓

GWP : Global warming potential PED : Primary energy demand W : Water

L : logic M : memory ⇔ : full coverage (PED;GWP;W) ↑ : bottom-up ↓ : top-down ⇅ : hybrid ⊖ : not available ✓ : included ✗: excluded

GLO : Global USA : United States of America CN : China TWN : Taiwan UK : United Kingdom

† : implicit, deduced by the authors ‡ : direct communication with the authors ⋆ : not peer-reviewed (scientific literature only)

◃ : back-end can be taken into account in their database if needed

3.3.2 The effect of technology downscaling on the environmental impacts of IC production

The distinction between technology types and nodes is generally performed in the scientific literature and in the LCA databases as illustrated in Table 3.3, because they aim at providing detailed datasets for LCA practitioners. We leverage this in order to highlight the effect of technology downscaling on the environmental impacts of IC production, as illustrated in Figs. 3.3(a) to (c).

If we first focus on the scientific literature, two leading sources of data cover technology nodes ranging from 0.25 μm down to 3 nm, i.e., respectively Boyd *et al.* [94] and Bardon *et al.* [95]. Even though they do not cover the same technology nodes, the large gap between these studies is mainly echoed in their different scopes and approach. While Boyd's study is intended to be cradle-to-gate LCA (including impacts related to the production of upstream materials such as raw materials, gases, etc.), the study of Bardon *et al.* is a gate-to-gate LCA. Although, the impacts of upstream materials for semiconductor grade remain largely unclear [111], it could explain in part the lower values obtained by Bardon together with the use of a bottom-up assessment method. The analysis for Figs. 3.3(a) and (b) is very similar. While Boyd's data shows an improvement in normalized PED with downscaling technology until 0.13 μm, followed by an increase until 32 nm, the study of Bardon *et al.* confirms the ascending trend on the last nodes from 28 nm down to 3 nm. Bardon *et al.* make clear that the accelerated increase in energy consumption is due to the growing number of interconnect layers in the BEOL, together with lithography, extreme ultra-violet (EUV), etching steps and low throughput process steps [95]. Similarly, Boyd also pointed out the "lengthening of the manufacturing process flow and concomitant expansion in manufacturing infrastructure and equipment" as a reason for the increase of environmental impacts per wafer [94]. Figs. 3.3(a) and (b) also reveal that the *mix* values fall in a range similar to other more detailed sources, even though in practice their use is of limited interest as technology node is not clearly stated. The gap observed between Boyd's work and the other sources is greater for water than for PED and GWP, as illustrated in Fig. 3.3(c). This could be explained by the fact that Boyd did not consider the revalorization of water (and UPW) through recycling, reuse or reclaim. We also acknowledge that less data are available for the water indicator, compared to PED and GWP. Finally, it seems that Bardon et al. [95] do not consider yields, which could explain why the values reported appear quite low compared to the other sources, in particular for advanced nodes. We would expect their estimates to shift upwards if the scope of their study is expanded.

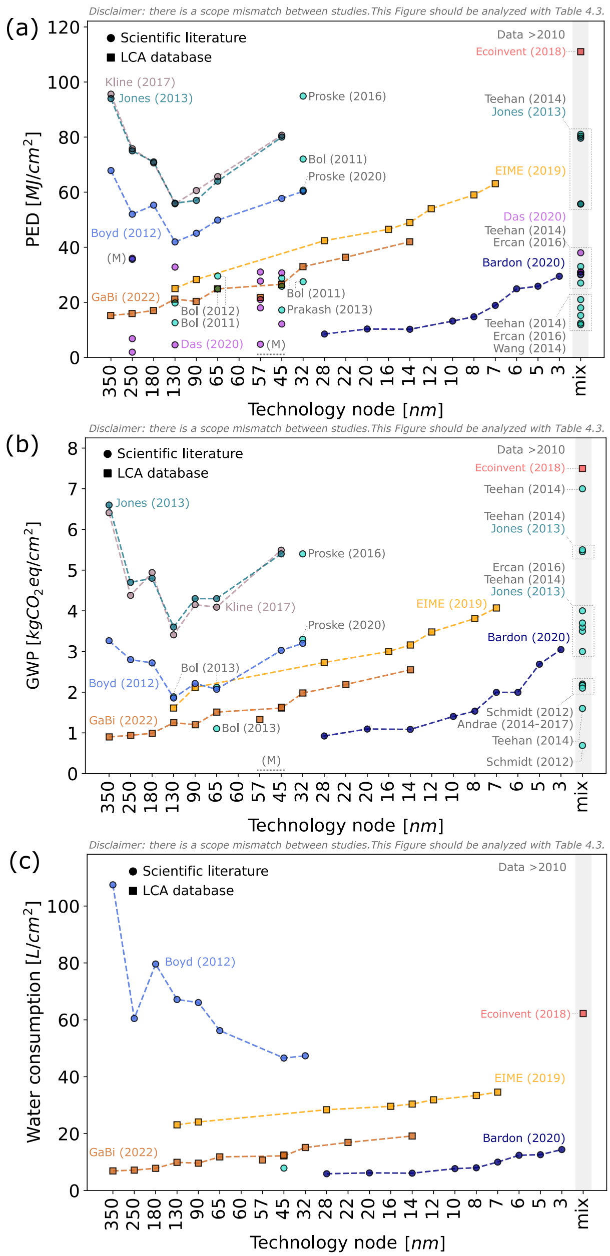

Fig. 3.3 Node-wise trends based on data from the scientific literature and the LCA databases. This shows the environmental impacts per cm^2 with respect to (a) PED, (b) GWP, and (c) water consumption.

If we then focus on LCA databases, a similar upward trend is observed for advanced nodes for both EIME database and Sphera LCA data. As already pointed out in the literature [19, 172], ecoinvent provides significantly higher values than other databases for IC production. Moreover, their functional unit is defined according to the weight rather than according to the die area (or package dimensions). Ecoinvent is thus probably not the best suited for IC environmental impacts modeling. Obviously, this must not be extrapolated to the rest of the database.

In conclusion, thanks to the fact that scientific literature and LCA databases both allow for a node-wise analysis as depicted in Figs. 3.3(a) to (c), we show that the environmental impacts per area are clearly increasing with technology downscaling below 0.13 μm. This is observed both in the scientific literature and in LCA databases, despite the scope mismatch. It also seems that this increase is accelerating for advanced nodes. In addition, we point out the significant inter-source data variations per technology node which is mainly due to the mismatch of scopes. This can be problematic as this variation will eventually end up in LCA results of ICT devices. Hence, we call for a unified modeling of environmental impacts of IC production. Providing specific details for the ten proposed features in LCAs of IC production would significantly facilitate the harmonization of the scopes in the future. Indeed, the lack of transparency significantly complicated our analyses.

3.3.3 The impact of pursuing advanced scaling for foundries

The previous section leveraged data from the first cluster and highlighted the increasing environmental impacts per area when shifting towards more advanced CMOS technology nodes. In this section, we focus on the second cluster to better understand the current situation in the foundries. Nevertheless, apart from a TSMC's press communication [190] suggesting that the 5-nm manufacturing process would consume about 1.48$\times$ more electricity than current mainstream manufacturing process, we found no public data disclosed by foundries to allow for a consistent estimation of the environmental impacts with respect to the technology node. Therefore, we analyzed the evolution of aggregated environmental impacts per area with respect to time instead of the technology node, as shown in Figs. 3.4(a) to (c). The total annual silicon area produced by each foundry was extracted from financial reports in order to normalize the global values extracted from the CSR reports for each environmental indicator. All details regarding the data extraction from CSR and the normalization are provided in Appendix C.

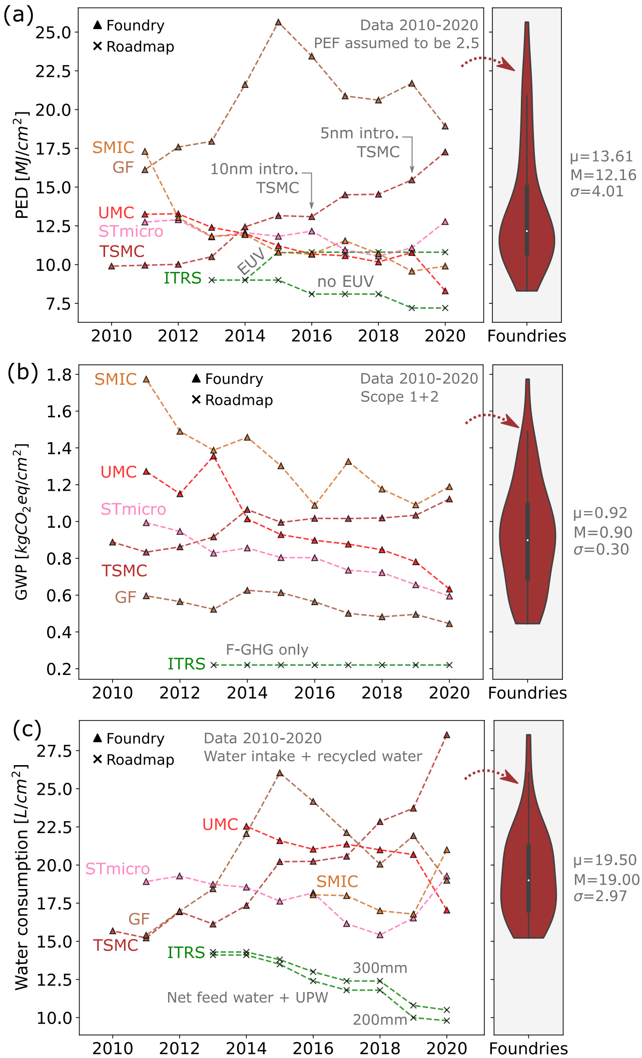

Fig. 3.4 Node-aggregated temporal trends based on data from foundry reports and industry roadmaps. This shows the environmental impacts per cm^2 with respect to (a) PED, (b) GWP, and (c) water consumption. The left sub-figure exhibits the data for each source while the right sub-figure reflects the aggregated data for all the foundries considered in this study (further used in Fig. 5.2).

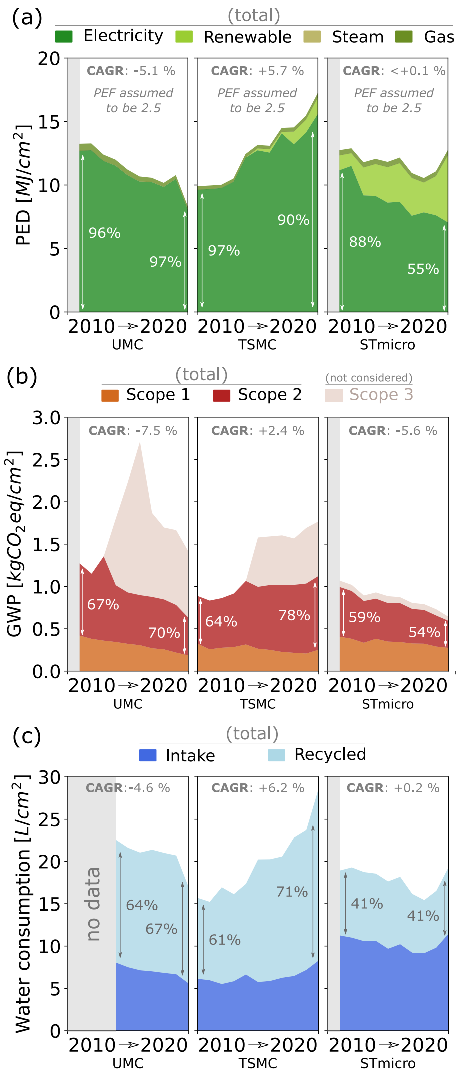

Fig. 3.5 Detailed view of the node-aggregated temporal trends for three foundries, i.e., UMC, TSMC and STMicro. This shows the detailed environmental impacts per cm^2 with respect to (a) PED, (b) GWP, and (c) water consumption. The share of electricity, scope 2 and recycled water with respect to the total is given on each sub-figure for the first and last year of available data in the period 2010-2020. Similarly, the CAGR of the total over that period is shown.

Figures 3.4(a) and (b) reveal two opposing trends: the impacts per area (slightly) decrease over the period 2010-2020 for most of the foundries while they increase for TSMC. This is even clearer in Fig. 3.5 where the compound annual growth rate (CAGR) is provided for UMC, TSMC, and STMicro as well as the composition of the aggregated values. Aside from the geographical location, the maturity of their process, and the output production volume, an important difference is the mix of technology nodes in the foundry production volume (although precise shares are not known). Indeed, TSMC is the only company in this study engaged in the production of technology nodes below 10 nm [170], which could well explain why it demonstrates a net increase in the impacts per area. This is not due to a lack of effort from the foundry to pursue efficiency but rather to the introduction of more demanding processes such as EUV lithography for scaling purpose [95, 190]. The high impact of EUV is also explicitly pointed out in ITRS roadmaps [185]. Yet, this analysis suggests that a reduction of the impacts per area is possible, provided that advanced scaling is not pursued. Indeed, other foundries keep demonstrating overall impacts reduction per cm^2, which could result from general manufacturing optimization. For instance, improvements in GHG abatement efficiency can lead to a decrease of scope 1 emissions [95]. Fig. 3.4(c) also depicts a clear increase in water usage for TSMC, but the trend is less clear than for PED and GWP for the other foundries. In fact, water consumption per cm^2 for SMIC and STMicro seem to increase after 2018. In all cases, the comparison between the foundry impacts and the roadmap targets in Figs. 3.4(a) to (c) shows that the industry is still facing challenges to reach the environmental targets. Note that a gap from a factor 2 to $4\times$ between ITRS roadmaps values and industry average was already acknowledged in [191] about 20 years ago.

The high share of electricity in the energy consumption is clearly shown in Fig. 3.5(a), ranging from 55% up to 97%. This likely explains why foundries show a strong commitment to shift towards a low-carbon energy mix as it is an effective solution to quickly decrease their scope 2 GHG emissions. Moreover, Fig. 3.5(a) suggests that the shift to low-carbon energy is mostly implemented by purchasing low-carbon electricity rather than producing it on-site. The overall relevance of such a system can be questioned as it prevents other sectors from acting similarly because the renewable capacity can be limited at the global or local scale [CP4]. Nevertheless, this could explain why the PED increase reported by TSMC is faster than its GWP increase in Fig. 3.5(b). The effect of using more renewable is illustrated by STMicro which effectively decreased the share of its scope 2 emissions while its PED remained almost stable, as illustrated in Figs. 3.5(a) and (b). Yet, it is important to stress that scopes 1 and 2 only provide a partial view of GHG emissions. As the perimeter of scope 3 is not defined in any of the five companies' CSR and is usually not provided, we could not include it. Even though some industries are starting to include scope 3 emissions, this should be seen as a lower bound as it

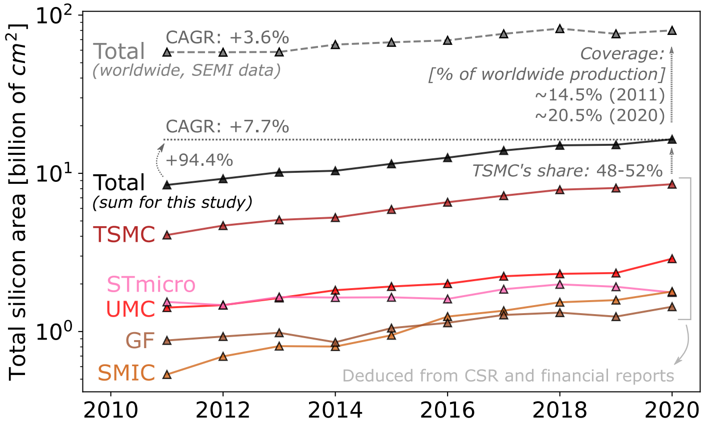

Fig. 3.6 Total silicon area production for the foundries considered in this study and for the worldwide production. Total annual silicon area produced by each foundry was deduced from CSR and financial reports (20-F, 1-F) by assuming a 90% load capacity.

is not yet common for the complex supply chain to report such information. This also explains why scope 3 varies significantly from one foundry to the other. For instance, Fig. 3.5(b) shows a high contribution for the scope 3 of UMC whereas it is marginal for STMicro. Companies and stakeholders must be incited to report it as this can contribute to a better modeling of environmental impacts. For example, thanks to the reporting of foundries regarding the recycling of water, it can be seen in Fig 3.5(c) that between 41 and 71% of the water is recycled. However, this is lower than the targets issued by the 2015 ITRS, i.e., 75% [185]. As recycling water consumes energy, it also points out the need to integrate all infrastructure impacts when analyzing the environmental footprint.

Finally, we compare the production volumes of foundries included in this study with the worldwide production of silicon area, as reported by SEMI[4] [192] in Fig. 3.6. From 2010 to 2020, this yields a coverage ranging from 14.5% to 20.5%. Consequently, we do not claim a full representativeness of the sub-sector, but it is still significant and covers key manufacturers in the field. Unfortunately, the data for Samsung, Intel and Micron are either too aggregated or not available, which prevents us from including them in this study and from reaching a higher coverage, i.e., close to 50%. Including Samsung in further studies would be of great interest

[4] SEMI data includes front-end fabs and foundries such as TSMC, UMC, GF, SMIC, Samsung, Intel, Toshiba, Micron, SK Hynix, Powerchip, Texas Instruments, STMicro, Fujitsu, NXP, Infineon, among others. Data are for semiconductor applications only and do not include solar applications.

because it is the second manufacturer of sub-10-nm ICs, as TSMC currently manufactures more than 90% of these ICs [170]. The total production for foundries considered in this study shows a CAGR close to 7.7%, mainly driven by TSMC's production. At the world scale, the total area of silicon produced over the last 10 years keeps increasing with a CAGR close to 3.6%, as illustrated in Fig. 3.6.

3.4 Discussion

In this section, we discuss the known limitations and compares our results with other studies.

3.4.1 Limitations

An important limitation of this study is the uncertainty related to the extraction of data in CSR reports from foundries. We came across the same issue in [JP4] but unfortunately, this is inherent to current CSR reporting. More transparency is needed, together with specific environmental data and reporting units allowing an efficient use of the results. A general lack of important information about assumptions or scope is also observed in the scientific literature, which significantly complicates comparison between studies. Again, a better standardization in reporting is needed to be able to eventually harmonize the scopes of future studies. A straightforward illustration of this limitation can be observed with the emission scopes terminology. As this terminology is specific to the GHG protocol, LCA studies usually do not detail their scope according to it whereas the CSR reports of foundries systematically do. Among the proposed features in Table 3.1, *infrastructure* could refer to a subpart of scope 2 whereas *upstream materials* could rather relate to scope 3. There is however no direct mapping between the proposed features and the emissions scopes terminology. Even if Table 3.1 does not only focus on the carbon footprint evaluation, it may be useful to have a more explicit link with the emissions scopes.

Then, the list of key features proposed in Table 3.1 is not an exhaustive list. In fact, reporting additional features such as wafer throughput would also be of interest although this information is almost never disclosed despite its significant influence [95]. Similarly, the consideration of non-production runs[5] and tool utilization[6] should also be explicitly reported, as they can contribute to the truncation error [99, 95]. Nonetheless, Table 3.1 already provides a starting point for a better standardization and transparency of future LCAs of IC production.

[5]For instance, a test run before a production run to ensure that everything is ready.
[6]Tools are not used 100% of the time. Idle times should therefore be accounted for.

Although it is tempting, the direct comparison between results presented in Fig. 3.3 and Fig. 3.4 should be avoided. In fact, the performance of each foundry in Fig. 3.4 depends on a variable (and unknown) mix of technology nodes, with associated volumes of production. Nonetheless, it is surprising to observe lower values per area unit with a top-down approach, while it is usually assumed that bottom-up approaches tend to underestimate the actual impacts. This observation suggests that inconsistency exists in the models, hence calling for more research to bridge the gap between bottom-up and top-down evaluation for IC environmental footprint.

Next, the relevancy and usefulness of computing a median or an average value for each indicator in Fig. 3.4 could be questioned. These values could also be weighted by the market share of each foundry to have a more representative estimate of the effective impact per area unit, which was not done here. Nonetheless, we chose the most simple and conservative method, which already provides a first attempt to benchmark environmental impacts of IC production with top-down data directly from the foundries.

Finally, even if we have reported the presence of dependencies in Table 3.3, it is not clear to what extent they affect the results over time. It seems that the majority of current models and estimates are based on the extrapolation of a few historic models, i.e., Boyd, Krishnan, etc. This is a real problem because they may have become a very distorted picture of the current impacts, supporting the urgent need for updated models and comparison with on-site measured data.

3.4.2 Comparison with other studies

Due to the scarcity of recent studies on the topic, the potential for comparing the results is limited. Yet, we found two very recent studies on a similar topic to compare our results with. The first study [193] focuses on environmental data in the semiconductor[7] industry and was published in February 2023 [193], hence providing material for a comparison both in terms of methodology and data. The second study [194] was published mid-2022 and provides brand new data for the manufacturing energy footprint of ICs and packages, which were not included in our initial review. This therefore offers a very interesting opportunity to demonstrate how new data compares to our quantitative analysis.

[7]Semiconductor manufacturing is broader than integrated circuits manufacturing, as clearly explained in [JP4]. For instance, it also includes the manufacturing of discrete electronic components.

Comparison with Wang et al. [193]

Wang et al. [193] surveyed the sustainability reports of twenty-eight semiconductors corporations and summarized the absolute and relative environmental impacts over the period 2017-2021. The methodology is very similar to one developed in a prior work we co-authored [JP4] (but not included in this thesis), even if we focused only on absolute environmental impacts of semiconductor corporations physically based in Taiwan over the period 2015-2020. Both studies share close conclusions for absolute impacts, as the GHG emissions, the energy use and the water consumption are all increasing over time. Moreover, these two analyses clearly confirm that electricity consumption is the main energy source for semiconductor manufacturing, as illustrated in Fig. 3.5. In fact, we showed in [JP4] that electricity consumption accounts for more than 94% of final energy consumption, which is further supported by [193] where the share of electricity consumption exceeds 85% for most corporations. In addition, Wang et al. [193] confirm the very low share of renewable energy used in semiconductor manufacturing, i.e., less than 3% of the total energy use. Yet, the share of renewable energy for STMicro is reported to be almost nonexistent in [193] compared to what is reported in their sustainability report and in our analysis.

In addition to absolute impacts, Wang et al. [193] also provide the environmental impacts per unit area of product for the three indicators from 2017 to 2021. However, they only provide average values for the year 2021 [193], whereas in our case we only have data before 2020. This prevents a year-to-year comparison. Nevertheless, as we consider an average of values over ten years in our study, we argue that the comparison can still be interesting, even if it is just to compare the order of magnitude. With this limitation in mind, the water use, energy consumption, and GHG emissions obtained by Wang et al. [193] are respectively, 8.22 L/cm^2, 1.15 kWh/cm^2, and 0.84 $kgCO_2eq/cm^2$. The comparison is straightforward for GHG emissions as the scopes are identical (scope 1 and scope 2). However, as the energy is not provided in primary energy in [193], we convert our results back to final energy consumption to ease the comparison. Finally, in our study we considered the total water consumption including the recycled water, as shown in Fig. 3.5(c). On the contrary, Wang et al. [193] did not consider recycled water. We therefore isolate the intake water in our results to allow for a fair comparison. Table 3.3 gives the comparison factors between both studies.

The comparison in Table 3.5 clearly shows similar estimates for the three indicators, even though the two studies were carried out in parallel and with no interaction between the authors. Our estimates are generally higher (up to +30%) than estimates from [193], but we consider an average of values over 10 years and we include foundries showing higher impacts per area, e.g., TSMC. The significantly higher value for water use is clearly explained by the inclusion of the recy-

Table 3.5 Comparison of environmental impacts per area unit in cm^2.

		Wang et al. [193]	This study [195]		Comparison factor†
Indicator	**Units**	Mean value	Median value	Mean value	
GWP	$kgCO_2eq/cm^2$	0.84	0.90	0.92	1.1
Energy	kWh/cm^2	1.15	$1.35^{\diamond}$	$1.51^{\diamond}$	1.3
Water	L/cm^2	8.22	(19.00)	(19.50)	(2.4)
			$8.49^{\triangleleft}$	$10.86^{\triangleleft}$	1.3

† : ratio of the mean ◇ : converted back to final energy (9 $MJ_{primary}/kWh_{final}$)
◁ : considering only intake water

cled water. Considering only intake water reduces the gap between both analyses and bring our estimates in a range comparable with the two other indicators. The higher level of details provided in [193] regarding the different water sources significantly contributes to improve the understanding of water use in semiconductor manufacturing. Future works would benefit from such a clear distinction between the different sources of water, including the clear split with UPW.

Comparison with Nagapurkar and Das [194]
Nagapurkar and Das [194] carried out economic LCA and conventional LCA of IC manufacturing and assembly processes with the OpenLCA software and the ecoinvent v3.5 database. They used the latest bill of materials manufacturing data obtained in a state-of-the-art IC manufacturing cost software tool developed by IC Knowledge, LLC and focused on a technology nodes of 22–20 nm and 70–68–45 nm for logic and memory IC, respectively. We further characterize the scope of their study in Table 3.6 according to the ten features proposed in this chapter to ease the comparison with the studies already included in our review.

The study finds out that the total cumulative energy demand[8] (CED) estimates of IC manufacturing ranged from 9 to 38 MJ/cm^2, with a standard deviation of 35%. These values fall in the lower range of the values identified during the review, between the estimates from Bardon et al. [95] and Sphera LCA. However, they include both front-end and back-end, which was not the case for the majority of the data depicted in Fig. 3.3. The lower values can be partially explained by the fact that (i) the impacts of the infrastructure are not taken into account, (ii) the study takes a fully bottom-up approach, and (iii) yields may not be included. Nevertheless, this comparison clearly points out the usefulness of our review approach, combining both qualitative and quantitative considerations.

[8]The CED calculates the total primary energy use for the generation of a product or throughout the life cycle [196].

Table 3.6 Characterization of the scope of Nagapurkar and Das [194] according to the ten features defined in Table 3.3.

Feature	Scope characterization
(1)	Front-end and back-end are included
(2)	Logic: 22–20 nm Memory: 70–68–45 nm
(3)	The study considers 300mm wafers
(4)	Assumptions about the yield are never disclosed in the study, which questions whether it is included or not. As they provide results in cm^2/wafer, we would assume that yield is not included. However, as they consider the back-end processing, they could have included the yield upfront of this step
(5)	The impact of the manufacturing infrastructures are not taken into account
(5)	It is not clear if the environmental impacts of upstream materials are considered or not
(6)	The geographical location is assumed to be in the US
(7)	The only environmental indicator in the study is CED (equivalent to PED). Yet, they also considered economical costs
(8a)	Process details are provided in the supplementary material, which is very interesting
(8b)	The normalization by cm^2 is clearly provided
(9)	A bottom-up approach is used
(10a)	The study performs the LCA based on the latest bill of materials manufacturing data provided by IC Knowledge, LLC
(10b)	Little (or none) dependencies to previous literature
(–)	The use phase was included in the specific case of the DRAM IC (contributing to about 28% in the total CED), which we should remove for the comparison

3.5 Summary

Improving the modeling of the environmental impacts occurring during the production of ICs becomes critical, as digitalization is developing fast. This is further supported by the high share of environmental impacts associated with IC production in the results of existing LCAs of ICT devices. However, although previous works already offer important insights on the topic, there is no clear consolidated understanding in the literature. In this chapter, we addressed this gap in two successive steps. First, we carried out an extensive literature review to identify key sources of LCA data with respect to three environmental indicators, i.e., energy consumption, carbon footprint and water consumption. Then, we conducted in-depth analyses to improve the current understanding of environmental impacts for IC production, both from qualitative and quantitative aspects. This revealed the existing variation introduced by the mismatch of scopes between sources and the effect of technology downscaling on the environmental impacts per cm^2, which brings useful insights for future LCA of IoT and ICT devices. Moreover, by defining ten specific objective features to characterize the scope of LCA for ICs, we propose a first step towards a better standardization of studies in this field. This aims at facilitating scope harmonization in the future and improve the general understanding of environmental impacts of IC production.

4

Full-scope cradle-to-grave LCA of a real-life deployed IoT solution

The earth is what we all have in common.
– Wendell Berry

In the previous chapters, we highlighted the critical need to consider the environmental impacts generated by the production of IoT devices, together with the need to pay particular attention to the presence of ICs due to their high impacts. However, cradle-to-gate LCA of IoT devices fall short from providing a comprehensive picture of the environmental impacts generated by IoT devices throughout their life cycle. Indeed, the remaining life-cycle phases should also be considered, from cradle to grave.

Consequently, the third step of this thesis further extends the scope of the analysis by including more life-cycle phases and more environmental indicators. On the contrary to Chapter 2, this chapter focuses on a single specific *IoT solution*[1] but

[1] We use the terminology *IoT solution* to define all the hardware, software, and necessary elements or services required to implement the different layers of the IoT application. IoT devices are hence only a part of the whole IoT solution.

significantly deepens the modeling for each phase of the life cycle. In fact, we conduct a detailed full-scope cradle-to-grave LCA over multiple indicators, and we considered a real-life deployed IoT network for smart public lighting in Wallonia, Belgium rather than conducting the LCA based on synthetic or hypothetical operating conditions. A key objective of this chapter in the context of systematic LCA for the IoT is to evaluate the gaps existing between full LCA and streamlined LCA approaches.

This chapter is organized as follows. First, we explore the state of the art in Section 4.1 to identify already existing full-scope and multi-indicator LCAs for IoT solutions. Then, Section 4.2 describes the methodology and details the modeling assumptions underlying the full-scope LCA. Next, Section 4.3 presents and interprets the results of our case study. Finally, Section 4.4 discusses known limitations, provides additional end-of-life considerations, and compares results with the streamlined carbon footprint evaluation obtained by using the hardware profile framework in Chapter 2.

4.1 Context

This section contextualizes the objectives of this chapter with respect to the state of the art.

4.1.1 Related Works

Among the studies identified in Chapter 2 and focusing on the environmental impacts of IoT solutions, only a few consider a full-scope analysis with multiple indicators [93, 127, 129, 45, 197]. We summarize the main contributions and conclusions of these works below.

In 2004, Dubberley et al. [197] carries out the cradle-to-grave LCA of an smart lighting system using a distributed WSN. They point out the high contribution of PCB and ICs for several impact categories. Furthermore, the LCA results are used to support the choice of battery for the remote sensors or the choice of materials, i.e., to support eco-design. However, even if they pioneered the use of LCA for WSNs, the use of ICT infrastructure for transferring data to the cloud is not included. This is understandable because WSNs may operate with or without internet connection [198].

Lelah et al. [93] were one of the first study arguing for the use of multi-criteria LCA on the complete system, including the use of ICT infrastructure (private and mutualized) to transfer data. In their pioneer study on waste management using M2M product service systems, they consider realistic use scenarios derived from field studies. The use of the LCA methodology in their case is totally driven by the need for a quantitative tool to support the eco-design of different IoT scenarios, decrease the burden generated by the proposed solution, and formulate recommendations for decision makers. The system under study has heterogeneous power sources (the sensors are battery-powered, the gateways use solar energy harvesters, and the ICT infrastructure is powered by the grid only), but the results clearly show that the manufacturing phase dominates, compared to the use and installation phase. Moreover, they highlight interesting cost-shifting phenomenon between different impacts categories such as GWP and raw material depletion. More importantly, they mention the need for further work and foster the consideration of fully commercialized services.

Similarly, Bonvoisin et al. [127, 129] also implement and recommend the use of full-scope LCA. In particular, they also take into account the burden occurring during the deployment, the maintenance, and dismantling phases. They show the importance of adopting a system-level perspective and provide an environmental assessment method for WSNs, which can support the eco-design of relevant alternatives. By pointing out the presence of dilemmas due to the diverse nature of the environmental impacts, they support the relevancy of considering several impact categories for the LCA of WSNs. Moreover, they explicitly mention that "optimization services must systematically be the object of a multi-criteria environmental assessment along their life cycle" to evaluate if they actually lead to impact reduction. It is not surprising to see strong similarities between these three studies as they are conducted by the same research group on the same case study.

Quisbert et al. [128] proposes an adapted cross-typed life-cycle modeling approach for the environmental evaluation of IoT solutions. As the studies of Lelah et al. [93] and Bonvoisin et al. [127, 129], the main goal is to support the eco-design of IoT solutions by taking into account the IoT hardware and the energy consumption of the mutualized ICT infrastructure. More specifically, the author highlights the importance of data-driven approaches for the eco-design of IoT systems and provides general guidelines for the eco-design of IoT devices in his PhD [45]. However, only two impact categories are considered and the LCA is focused on the technical solution without considering its maintenance, or deployment for instance. Additional general guidelines for the sustainable deployment of a large number of WSN networks are proposed in [46, 47], which point out the need to minimize (i) the embodied energy and carbon footprint of the WSN production, (ii) the ecotoxicity of the WSN e-waste, and (iii) the Internet traffic associated to the generated data.

A very detailed study was published by Ingemarsdotter et al. [12] in 2021. The main goal of their study is to better understand when and how embedding IoT hardware into products to support circular strategies makes environmental sense [12]. In fact, they evaluate the *net* environmental impacts of using of IoT to support circular strategies through a case study on truck tires in the Swedish context. They use a full-scope and multi-indicator LCA approach to quantify both the potential environmental savings in the different life cycle phases and the environmental impacts generated by the additional technology needed for their application (including the impacts of data transfer). Although IoT devices are modeled using SimaPro and ecoinvent, without considering the PCB, and with important simplifications regarding some electronic components such as ICs, their study remains very useful, well documented and supported by sensitivity analyses. They use the ReCiPe 2016 (H) method and its weighting step to obtain a single score indicator.

Finally, Manz et al. [130] conduct a full-scope multi-indicator LCA on the specific case study of a smart smoke detector. They use SimaPro and ecoinvent with the ReCiPe 2016 Midpoint LCIA method and provides environmental impacts over six categories, i.e., including GWP, ecotoxicity (terrestrial, freshwater, and marine), and resource scarcity (mineral and fossil). Custom models are developed in ecoinvent to capture the environmental effects of the alkaline batteries needed for the smart detectors and they also included the end-of-life of the device in their scope. However, several gaps can be identified. First, they acknowledge that several electronic components are not included in the study, including ICs and communication modules. Then, the deployment, maintenance, and decommissioning phases are not considered. Finally, they consider point estimated and non peer-reviewed study to estimate the energy of data transfer on the ICT infrastructure. Nonetheless, the authors provide an extensive supplementary material with the LCI of their study, which is a very good practice to foster transparency.

As highlighted in these studies, considering a full-scope analysis including the use of the ICT infrastructure[2] to transfer data should be done systematically in the context of IoT solutions. In addition, the use of multi-criteria LCA helps identifying impacts transfer, which is important to go beyond carbon footprint considerations. This is especially important for electronic devices as impact transfers can occur from energy or carbon footprint to resource depletion for instance. Nonetheless, the majority of these studies focused on battery-powered IoT edge devices and several studies become outdated. Furthermore, we stress out again the overall clear lack of details regarding the LCA modeling in these studies. Even if the results are very interesting, this limits their uptake and the understanding of modeling assumptions.

[2] The ICT infrastructure could be private or mutualized.

4.1.2 Objectives

To build upon these works, the main objective of this chapter is to carry out a full LCA for a real-life IoT solution powered by the electrical grid. The analysis needs to account for all life-cycle phases, including the impacts of transferring data on the ICT infrastructure, the deployment, the maintenance, and the decommissioning. Moreover, details about modeling assumptions should be provided to foster transparency and in-depth understanding of the results. The second objective is to compare the results of a streamlined analysis with the results of a full LCA to better understand *when* and *how* these approaches should be used in the context of systematic LCA for the IoT.

4.2 Methodology

In this chapter, we carry out a detailed full-scope LCA to evaluate the direct environmental effects of a real-life IoT network on a specific case study of IoT smart public lighting. We use a bottom-up attributional LCA approach, based on real-life scenarios according to one public road in Belgium.

4.2.1 Description of the IoT case study

The IoT solution is designed by an IoT company[3] who is developing and selling smart lighting solutions at large scale to operators which are in charge of (public and private) lighting infrastructures. This solution implements the remote control of public lights (mainly remote dimming) and enables predictive maintenance for each streetlight. The IoT solution gathers two types of nodes in the IoT area network, namely (i) an IoT node per light fixture, and (ii) a gateway intended to connect several nodes to the cloud through a mobile 4G connection. One gateway usually serves about one hundred IoT nodes, which are connected in a mesh topology using the Wirepass protocol (2.4 GHz) [199]. The IoT solution does *not* implement edge sensing for the real-time detection of pedestrians or cars. Several sites are equipped in Belgium but we consider the site with the largest number of IoT nodes among the sites shared by the company. In our case, the IoT solution is deployed over approximately 3 km, as illustrated by the green portion in Fig. 4.1.

[3] The company wants to remain anonymous for confidentiality reasons but authorized us to publicly share the majority of data used in the LCA.

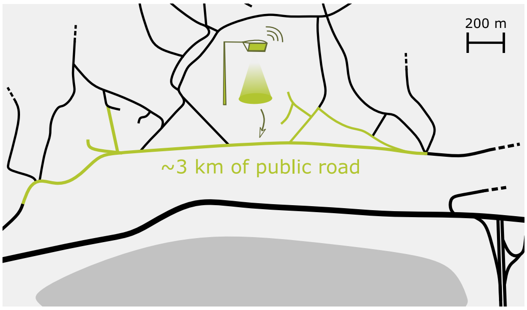

Fig. 4.1 Schematic map of the deployment site. The green portion of the public road is equipped with the IoT solution implementing smart lighting.

4.2.2 Modeling assumptions

This section provides the main modeling assumptions underlying the LCA carried out in this chapter. Simplified bill of materials for both the IoT node and the gateway are provided in the Appendix D.

- **Goal:** The goal of this LCA is to assess the environmental impacts of a real-life deployed IoT solution for smart public lighting.
- **Functional unit:** The functional unit is a real-life IoT network with $N_{nodes} = 108$ IoT nodes and $N_{gateway} = 1$ gateway, working 24/7 during 10 years, and controlling the public lighting over approximately 3 km of public road.
- **System boundaries:** We consider a cradle-to-grave system including life-cycle phases and processes from raw-material extraction, production, transport, deployment, use, maintenance, decommissioning, and end of life, as illustrated in Fig. 4.2. The use of existing ICT infrastructure for data transfer is also taken into account, but the impacts associated with the production of this infrastructure are not included.
- **Impact categories:** Twelve impact categories are covered, mainly from the ReCiPe 2016 v1.1 (H) midpoint and the CML 2001 methods. The complete list is provided in Table 4.3.

Although primary data is hard to access for ICT devices and electronic components [JP1], the major part of the data used in this study are provided by the company. In addition, the company answered a detailed survey designed by the authors to obtain the specific details needed to derive realistic modeling assumptions. In order to evaluate the parameter uncertainty of our modeling, we define a set of *low*, *typical* and *high* values for each parameter.

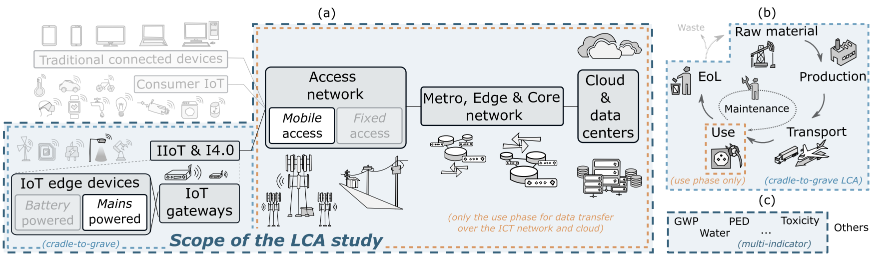

Fig. 4.2 Illustration of the system boundaries for the full-scope LCA carried out in this chapter. (a) Schematic IoT network representation. (b) Life cycle phases. (c) Impact categories. The complete list of indicators is provided in Table 4.3.

The Sphera LCA databases were used to model the **raw-material extraction** and the **production** of the different electronic components such as ICs, PCBs, passive components, casings, etc. As the majority of modules were not directly available in the database, custom models have been developed in Sphera LCA. This was the case for the 4G LTE connectivity module, the Bluetooth module, the WiFi dongle, the antennas, the Raspberry Pi 2, several system in packages chips involved in processing and memory tasks, and the GPS module. All materials used in our models are virgin materials, no recycled material.

Regarding the **transport**, all models are based on the joint consideration of distance and mass to be transported (in kg·km), where the mass considered is the sum of the product's mass and its packaging. The components are transported from China to the assembly site by container, and the intermediate steps between the dispatching site and the clients are modeled assuming a transport by truck, or plane for the worst-case modeling.

For the **use phase**, we consider both the nominal specifications from datasheets and the information from the company based on electrical characterization during operation. The power consumption for the gateway is ranging from 3 to 5 W (typical 4 W) whereas the IoT nodes consume between 0.3 to 1.92 W (typical 0.6 W). Both the nodes and the gateway are powered by the electric grid, as they are connected to the light fixture's main power supply through the Digital Addressable Lighting Interface (DALI) connection. The average Belgian electricity grid mix is used for the use phase.

For the **deployment and decommissioning**, we consider three vehicles (trucks), according to the procedure used in practice which requires two bumpers and one elevator if deployed on a highway. In the case of the gateway, a low load factor (about 1%) is considered as the gateway is generally handled separately from the rest of the IoT nodes deployed per batch. The average distance per IoT node and gateway is based on an estimate as no data could be found.

Similarly, because of a lack of data to properly model the **maintenance**, we consider the mean time between failures (MTBF) estimates for the IoT nodes and gateway provided by the company to capture the overhead in terms of IoT devices production and associated transport in order to fulfill the functional unit.

Regarding the **end of life**, a very basic model was considered by assuming that electronic parts would end up in an incineration plant whereas plastic parts would end up in a landfill. The actual end-of-life management is clearly badly understood, even by the company itself. Unfortunately, this is a common observation in LCA of electronics. The end of life strongly suffers from a lack of data and considerations although this could have detrimental effects in categories such as ecotoxicity [JP1]. Consequently, our modeling most likely underestimates the actual end-of-life impacts.

4.2.3 Accounting for the environmental impacts of transferring data over the ICT infrastructure

An important feature of ICT and IoT solutions is that they generally transfer data during the use phase[4], even if the amount of data can strongly vary from one solution to another. As pointed out in previous studies [93, 128, 130, 127, 129], the environmental impacts associated with these data transfers must be taken into account. In our case, the power consumption overhead due to the communication in the Wirepass mesh network is already included in the use phase power consumption. However, the environmental impacts of transferring data **over the existing ICT infrastructure** is not yet considered in our modeling and must be taken into account. This includes the data transfers from the gateway, to the telecom network, and to the cloud but also the data transfers for the regular over-the-air updates of the IoT network.

If the IoT solution is not implemented exclusively with private ICT infrastructures, transferring data over the existing ICT infrastructure leverages the *mutualized* infrastructure of Internet. An allocation key is hence required to allocate a part of the environmental impacts associated with the ICT infrastructure to the IoT solution under study. We chose an allocation key based on the data volume and we applied electricity intensity factor in kWh/GB, as this is the most common approach

[4]One may argue that data can still be used after the disposal of the *physical* IoT solution, but let's assume that *use phase* is used in a generic way here.

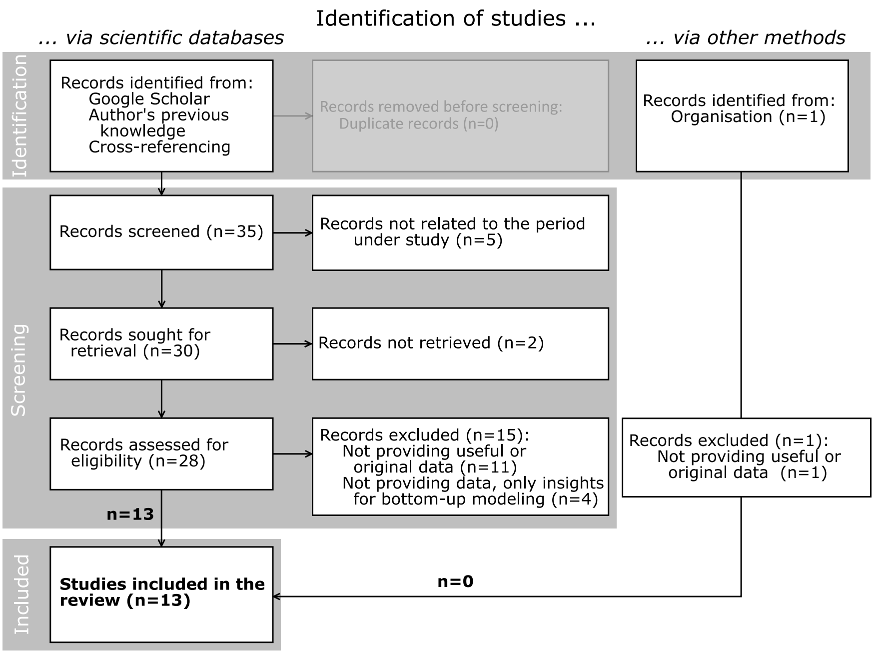

Fig. 4.3 Identification of relevant studies for the review of the literature on the energy intensity factors for data transfer. Screening and sorting of studies are based on exclusion criteria specified in the chart. The final list of studies included in the review is provided in Table 4.2.

used in both the scientific and grey literature [21, 200]. Nevertheless, several studies report different factors, which can diverge by a few orders of magnitude [200]. There are mainly two reasons for this high variation. First, rapid energy efficiency improvements are continuously decreasing the energy intensity of transferring one gigabyte (GB) of data on the infrastructure [21]. Second, all studies do not cover the same scope, similarly to what was highlighted in Chapter 3 in the case of IC production. In the case of data transfer on the ICT infrastructure, the common system boundaries are the access network (AN), the metro-core (MC) network, and the datacenters (DC) and cloud. Literature reviews on the energy intensity of data transfer have already been carried out in the past [21, 200]. Yet, the the best of our knowledge, the most up-to-date review was conducted in 2017 by Aslan et al. [21] and focused only on fixed-line transmission, whereas a 4G mobile connection is used in our case study. Consequently, we conduct a literature review to identify energy intensity factors used in the recent scientific literature, from the access network up to the cloud.

Table 4.1 Summary of the energy intensity factors considered for data transfer on the ICT infrastructure.

	Energy intensity [kWh/GB]		
ICT infrastructure	low	typical	high
Radio access network (4G)	0.1 [201]	0.15 [202]	0.27 [202]
Metro and core network	0.01 [21]	0.06 [21]	0.08 [203]
Data centers and cloud	0.027 [204]	0.085 [204]	0.15 [183]

We include top-down, bottom-up, and hybrid approaches for studies published after 2010 and providing energy intensity in kWh/GB. We identified 36 studies based Google Scholar, cross-referencing and author's previous knowledge. Additional details are provided in Appendix D. According to the exclusion criteria provided in Fig. 4.3, we end up with the 13 studies listed in Table 4.2. The data provided in these studies was then clustered according to its scope and reference year, as illustrated in Fig. 4.4. Significant improvements in energy intensity can be seen over the years, especially for the access network and the data center. Based on the review, a range of values is then selected for each sub-part of the infrastructure to define the energy intensity factors used in the context of the full-scope LCA. The selection of the final factors among all values available in the review is based on technology relevance (4G for the radio access network for instance) and year of assessment (priority is given to recent studies). These factors are provided in Table 4.1 and highlighted in Fig. 4.4 to put them in perspective with other energy intensity factors available in the literature. All details of the review (including data and scope characterization) are provided in Appendix D. The Belgian electricity grid mix is used as energy source for the electricity consumption of the access, metro, and core network. For the data center part, the average European electricity mix (EU-28) was chosen.

Table 4.2 Studies included in the review of the energy intensity needed to transfer data on the ICT infrastructure.

Study	Year	Methodology	Scope			Study ID
			AN	MC	DC	
Baliga et al.[205]	2011	Bottom-up	(✓)	✓	(✓)	(0)
Schien et al.[203]	2013	Bottom-up	✓	✓	✗	(1)
Coroama et al. [206]	2013	Bottom-up	✗	✓	✗	(2)
Schien et Preist [207]	2014	Bottom-up	✗	✓	✗	(3)
Golard et al. [202]	2022	Bottom-up	✓	✗	✗	(4)
Teehan [18]	2014	Top-down	✓	✓	✓	(5)
Malmodin et al. [71]	2018	Top-down	✓	✓	✗	(6)
Pihkola et al. [201]	2018	Top-down	✓	✗	✗	(7)
Malmodin et al. [208]	2012	Hybrid	✗	✓	✗	(8)
Malmodin et al. [22]	2014	Hybrid	✓	✓	✓	(9)
Coroama and Hilty [200]	2014	Hybrid	✓	✓	✗	(10)
Andrae et al. [204]	2015	Hybrid	✓	✗	✓	(11)
Aslan et al. [21]	2017	Hybrid	✓	✓	✗	(12)

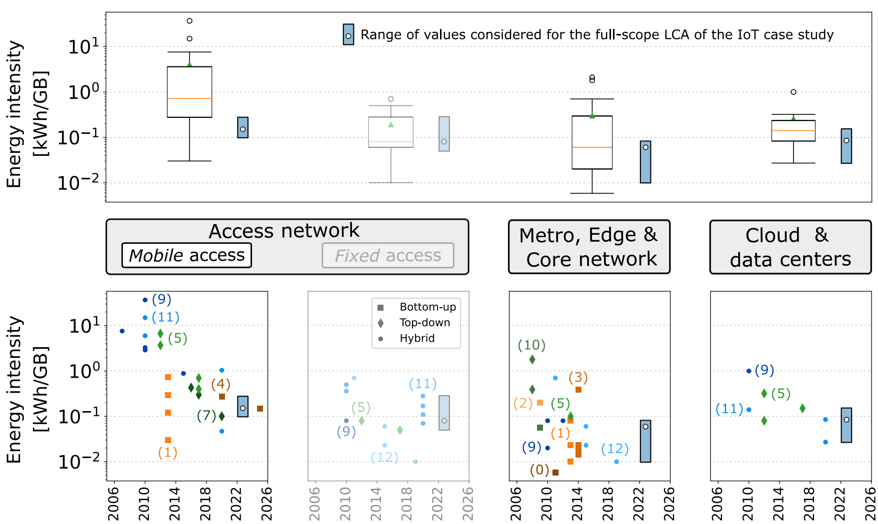

Fig. 4.4 Energy intensity factors in kWh/GB for the studies included in the review. Each factor is associated with its reference year, which usually differs from the publication year. The study identifiers (ID) are provided in Table 4.1.

4.3 Results

The characterization and normalization results for the set of *typical* parameters are provided in Table 4.3. They are further broken down per life-cycle phases in Fig. 4.5(a) for the full network as defined in the functional unit, and in figures 4.5(b)-(c) for the IoT node and the gateway, respectively. The first conclusion is that the use phase is clearly dominating the environmental impacts (about 80%) for the majority of indicators, except for the terrestrial ecotoxicity, the terrestrial acidification, the human toxicity (non-cancer), and the abiotic depletion potential, where the production reaches at least 50%. This observation regarding the use phase is not surprising for IoT nodes powered directly by the grid as they usually have less power consumption constraints than battery-powered IoT nodes which have a strict power budget [144, 93]. It also clearly appears in Fig. 4.5(a) that the impacts generated by the IoT nodes are responsible for the highest share of the network, generally more than 90%.

The impacts of transport, deployment and decommissioning turn out to be extremely low compared to the other phases of the life cycle, mainly due to the very low weight of the products. Yet, Fig. 4.5(c) shows the effect of a low load factor of vehicles for the gateway. Indeed, the deployment and decommissioning phases reach almost 20% of the impacts for some indicators whereas they were almost invisible in Fig. 4.5(b). This points out the benefits of batch deployment as implemented for the IoT nodes.

The impacts of the data transfer from the gateway to the data center through the ICT infrastructure appear to be extremely low compared to the total impacts (less than 0.1%). This is mainly due to the very small amount of data transmitted by the gateway. This conclusion cannot be generalized to all IoT systems as it strongly depends on the amount of data generated by the application as well as on the data management policy. It is worth to highlight the sober data traffic over the ICT infrastructure for this IoT solution, i.e., about 50 MB per gateway per month.

The normalization results are provided in Table 4.3 in order to provide perspective and ease comparison. The reference situation for the normalization step is directly taken from the ReCiPe and CML methods assuming a world-average impact in person equivalent for the year 2010. For instance, the reference value for GWP is 7990.4 kg CO_2 eq. Table 4.3 shows that the environmental impacts of the IoT solution represent only a fraction of the reference situation. Yet, the highest relative contribution is observed for the abiotic depletion.

Table 4.3 Characterization and normalization result for the functional unit over the different impact categories considered in this study. The results are given for the *typical* set of parameters but the variations associated with the *low* and *high* bounds are provided.

Impact category	Abbreviation	Characterization$^{\triangleleft}$	Units	Uncertainty$^{\times}$[%] (w/o)	Uncertainty$^{\times}$[%] (w/)	Normalization$^{\triangleright}$[/]
Climate change*,†	GWP	1642.9	$kgCO_2eq$	$[-1;+3]$	$[-41;+176]$	0.21
Primary energy demand$^{\diamond}$	PED	64233.6	MJ	$[-0;+1]$	$[-45;+195]$	-
Terrestrial ecotoxicity†	T-EcoTox	769.5	kg1,4-DBeq	$[-3;+4]$	$[-20;+77]$	0.05
Terrestrial acidification†	T-Acid	2.0	$kgSO_2eq$	$[-2;+6]$	$[-28;+121]$	0.05
Photochemical ozone formation$^{\circ,\dagger}$	POF	2.1	$kgNO_xeq$	$[-2;+7]$	$[-37;+160]$	0.10
Land use†	LandUse	187.4	Annual crop.eq· y	$[-1;+1]$	$[-47;+201]$	0.03
Human toxicity, non-cancer†	HT-nc	59.9]	kg1,4-DBeq	$[-4;+7]$	$[-29;+117]$	<0.01
Human toxicity, cancer†	HT-c	0.9	kg1,4-DBeq	$[-2;+2]$	$[-39;+169]$	0.09
Freshwater eutrophication†	FE	<0.1	kgPeq	$[-0;+2]$	$[-42;+180]$	0.01
Freshwater ecotoxicity†	F-EcoTox	0.2	kg1,4 DBeq	$[-2;+5]$	$[-37;+156]$	0.01
Freshwater consumption†	F-Water	13.2	m^3	$[-0;+1]$	$[-43;+185]$	0.05
Abiotic depletion potential (elements)‡	ADP	<0.1	kgSbeq	$[-2;+10]$	$[-4;+19]$	0.61$^{\bullet}$

$\triangleleft$: characterization results (typical)

$\triangleright$: normalization results (typical), based on conventional normalization factors from ReCiPe† and CML‡ $\bullet$: Normalization factor for 2000

$\diamond$: renewable and non-ren. resources (net calorific value), from Sphera LCA $*$: excluding biogenic carbon (default) $^{\circ}$: human health

$\dagger$: ReCiPe 2016 v1.1 Midpoint (H) $\ddagger$: reserve base, from CML2001 - Aug. 2016

$\times$: Variation for the *low* and *high* bounds, relatively to the *typical* results. Ranges are provided without (w/o) and with (w/) the use-phase uncertainty, respectively. Uncertainty sources considered are limited to variability between objects, parameter uncertainty, and model uncertainty.

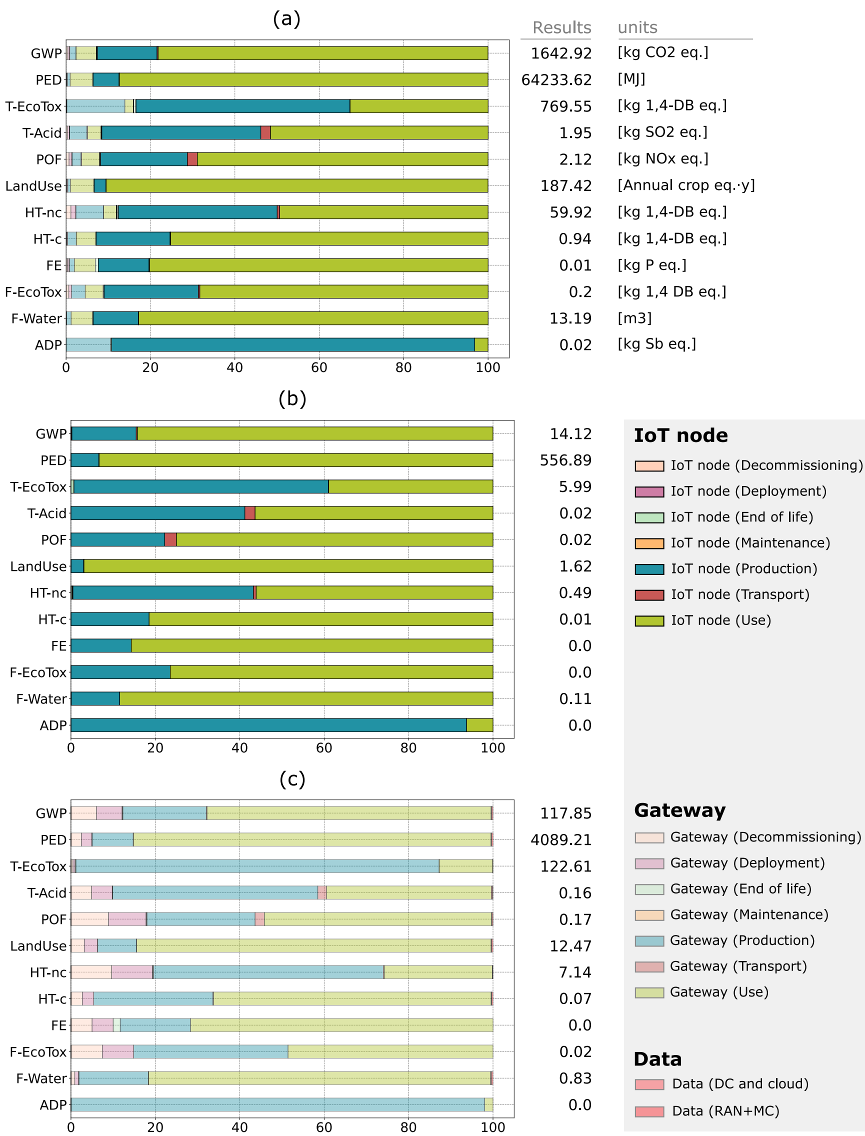

Fig. 4.5 Characterization results of the LCA for (a) the full network as defined in the functional unit, (b) a single IoT node, and (c) a single gateway.

4.4 Discussion

This section discusses the limitations of the full-scope LCA carried out in this chapter, together with eco-design considerations. Moreover, we compare the results provided by the full LCA and the ones provided by the hardware profile framework for the evaluation of the production carbon footprint.

4.4.1 Limitations

First of all, Table 4.3 shows that the uncertainty estimates between the *typical* and the *low* and *high* results can be significant. In particular, the uncertainty associated with the use phase is large, mainly due to the difference between the lowest and highest values from the datasheets for the power consumption, i.e., more than a factor 6× for the IoT node. Nevertheless, by using knowledge from the company regarding the effective power consumption of their IoT devices, the uncertainty can be significantly reduced as shown in the uncertainty column in Table 4.3. In addition, several modeling iterations have been carried out to reduce the uncertainty associated with the other life-cycle phases. We mainly used teardowns, hardware inspections, and interactions with the IoT company. For the majority of ICs, the exact silicon die area has been obtained through chemical desencaspulation, using the methodology detailed in [JP1]. This significantly reduces the uncertainty regarding the modeling of ICs as the evaluation of the die area is often challenging [126, 183, 209][JP1,JP2]. Additional details regarding the modeling and the parameters are provided in Appendix D.

Then, practical information regarding the deployment, the maintenance and the decommissioning were obtained through the company that is developing the IoT solution. However, they are not the ones deploying or maintaining the IoT network even if they have a good knowledge regarding how it happens in practice. Consequently, we could expected an underestimation of actual interventions associated with the IoT solution, leading to a potential underestimation of environmental impacts within this life cycle phases. Given their very low contribution in Fig. 4.5, it is not likely that they could became a hotspot but the study would greatly benefits from inputs of the operator that is maintaining the streetlight infrastructure. Indeed, these phases are almost never modeled (or badly modeled), which should be improved by conducting LCA with close interactions with the people deploying the solutions in real life. More generally, it is important to point out that the uncertainties discussed in this section are mainly limited to variability between objects, parameter uncertainty, and model uncertainty, which only covers a subset of all possible uncertainty sources listed in Chapter 1.

Finally, the results are limited by the naive modeling of the end-of-life, even though this is clearly mentioned in the assumptions. This issue is not specific to IoT, but rather a very recurrent problem in the LCA of electronics [93]. Indeed, assessing the environmental burden generated by the disposal of electronics is challenging. According to [210, 211], about 80% of WEEE are not documented nor collected for proper recycling. A wide majority hence ends up in developing countries where informal recycling and landfill occur, causing health and environmental concerns [212, 213]. The end-of-life of electronics has usually a low GWP contribution compared to production or use phases [19, 20], which does not necessarily hold for impacts in other impact categories such as freshwater, terrestrial and human ecotoxicity. However, we should be careful when using conclusions from previous works claiming that the end of life does not significantly contribute to the overall impacts because the modeling of this life cycle phase has always been very poor. Moreover, in practical IoT deployment scenarios, real-life working conditions can introduce the need for replacement [45, 127, 144] due to aging of components leading to the accelerated death of nodes. This is likely to contribute to the already increasing number of abandoned IoT *zombie* devices [113, 214], especially in outdoor environments with corrosion and varying temperature-humidity conditions. As previously explained, we used MTBF estimates provided directly from the company as an attempt to account for these issues, even if it only scratches the surface of the problem. Yet, no reuse, repair, or recycle scenarios were considered, mainly because of the lack of real-life examples from the company and the lack of relevant data. In general, it is clear that important work is needed to bring real improvements regarding the end-of-life modeling of electronics and IoT.

4.4.2 Comparison with the hardware profiles framework

Conducting a detailed full-scope cradle-to-grave LCA takes a considerable amount of time compared to a streamlined LCA, even with prior expertise [51]. Indeed, carrying out a full LCA requires knowledge of the tools and methods, teardowns to obtain a detailed BoM, several modeling iterations, more specific data, and interactions with the manufacturers or developers, among others. The use of streamlined approaches could therefore ease this first step towards environmental considerations for IoT solutions, as they could quickly provide coarse-grain estimates. However, the question whether these streamlined estimates properly anticipate the results obtained with a full analysis is still far from being investigated for the IoT, and for electronics products in general. In this section, we therefore compare the results obtained by using the hardware profile framework proposed in Chapter 2 and the specific LCA carried out in this chapter. The comparison focuses only on the carbon footprint evaluation of the production for the IoT node and the gateway, as limited by our framework. The associated hardware profiles are defined based on Table 2.2 and the BoM used for the specific LCA.

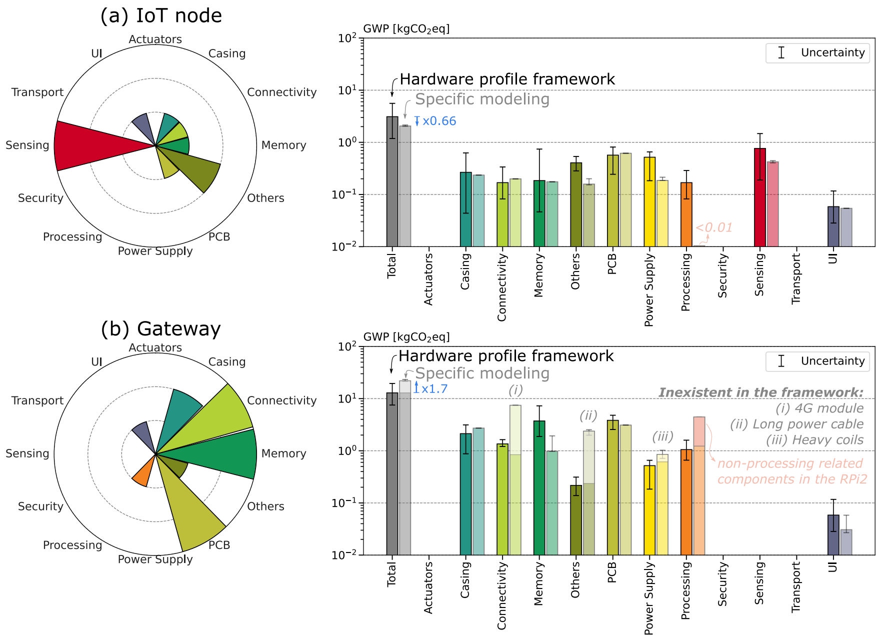

Fig. 4.6 Comparison of the carbon footprint results obtained through the hardware profiles framework and the specific LCA for the production of (a) the IoT node, and (b) the gateway.

Figure 4.6(a) shows that the IoT node is similar to a light hardware profile, although the sensing part is significant mainly due to the presence of the GPS module. On the contrary, the gateway is closer to a complex hardware profile, as illustrated in Fig. 4.6(b). Regarding the IoT node, the analysis of the overall carbon footprint evaluation reveals that the estimates provided by the framework are close to the results obtained with the full LCA. Indeed, the typical case falls within the variability boundaries. It can be explained by the fact that most of the components were modeled in the framework, or could be approximated with a relevant substitute. However, the situation is different for the gateway, as shown in Fig. 4.6(b). Although the total carbon footprint obtained through the full LCA is slightly higher than the higher bound provided by the framework, important gaps can be observed within several functional blocks. For instance, the full LCA yields a carbon footprint almost 5× higher than the higher bound of the framework for the `Connectivity` functional block. Underrestimation can also be observed for other functional blocks, e.g., `Others`, `Power supply`, and `Processing`. A deeper analysis of the BoMs reveals that some components of the gateway are simply not captured by the framework, therefore leading to a foreseeable undershoot in these functional

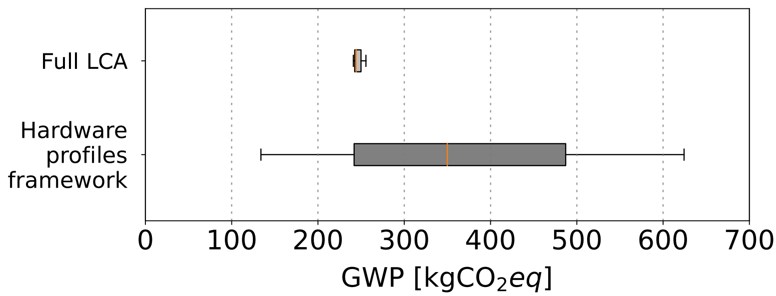

Fig. 4.7 Comparison of the carbon footprint evaluation for the production of the functional unit obtained through (a) the hardware profiles framework from Chapter 2 and (b) the full LCA conducted in this chapter.

blocks. This is the case for the 4G connectivity module, a long power cable, heavy coils, and the Raspberry Pi 2, respectively. When removing these specific components, the overall carbon footprint estimated with the hardware profile framework falls back within the range estimated by the framework. The origin of the discrepancies observed in these functional blocks can hence be explained. Nevertheless, this points out that the framework should be adapted to include a fully-integrated 4G connectivity module in a high-end HSL, for instance. Finally, this comparison also highlights that the hardware profile framework is good at estimating the overall carbon footprint of an IoT device, but not the best-suited approach to identify the hotspots and carry out eco-design on these devices. In that case, full LCA must be conducted as it is highly specific.

Let us mention that very detailed BoMs were available before applying the framework, as a specific LCA was first carried out. This should not be neglected as detailed BoM are not always available. In addition, BoM creation usually requires a significant amount of time due to the number of components and the scarcity of useful LCA-related information in current datasheets. Nevertheless, the streamlined carbon footprint estimate provided by the framework is obtained in a dozen of minutes, whereas full LCA can require weeks of work[5]. Obviously, the uncertainty is higher when using the framework but it can still provide a useful estimate. For instance, we illustrate in Fig. 4.7 the difference between a quick estimate of the cradle-to-gate carbon footprint using the framework and the result of the full LCA, for the functional unit under study. Given the higher number of IoT nodes (108:1),

[5]This remains faster than the design and development time generally required for a new IoT solution, which can support the integration of systematic LCA to support eco-design of these solutions.

results are similar to the ones in Fig. 4.6(a). This also reveals the importance of defining what limit of uncertainty is acceptable in the results according to the goal and scope of the study. In fact, striving for the smallest uncertainty usually requires many iterations, which could turn into a significant waste of time and efforts if this goes beyond what is needed. Defining a *sufficient tolerance* for the uncertainty appears to be a better approach, yet leaving open the question of what is *sufficient*.

In general, this demonstrates the usefulness of hardware profiles for the streamlined evaluation of the production carbon footprint of IoT devices, but also points out the need for specific modeling in order to improve the definition of the HSLs. A streamlined approach is therefore useful to foster the systematic integration of environmental considerations for the IoT, but our streamlined approach will remain relevant only with the continuous *background* support of full LCAs. We argue that it cannot and *should not* substitute to in-depth analysis in the long term, although it quickly provides quantitative data while requiring less resources and expertise. These are two different approaches and their goal should not be mixed up. This analysis could serve as a basis for further work on the hardware profile framework and helps understanding the trade-offs between results preciseness and accuracy, modeling approach, expertise, and time required for the assessment.

4.5 Summary

In this chapter, we extended the previous chapters by carrying out a detailed full-scope and multi-indicator LCA for a real-life deployed IoT solution powered by the electrical grid. Due to the current lack of comprehensive LCA for IoT devices, these results help to better understand the environmental impacts of an (industrial) IoT solution. Moreover, we carried out a review of the literature to select relevant energy intensity factors in order to model the environmental impacts of transferring data over the ICT infrastructure, from the IoT gateway to the cloud. In fact, previous studies always focused on a fixed access connection rather than a 4G mobile connection. In a second time, we compared the results of the full LCA with the carbon footprint estimates provided by the streamlined hardware-profile framework presented in Chapter 2. By doing so, we pointed out the trade-offs between streamlined and full LCA approaches, which is crucial to support systematic LCA in the field of IoT.

This chapter concludes the first part of this thesis, which was mainly dedicated to argue *why* the systematic assessment of the direct environmental effects of IoT solutions is needed, and *how* to foster it in practice. As introduced in Chapter 1, we mainly used the LCA methodology to "show in which parts of the life cycle it is particularly important to improve a product to reduce its environmental impacts" [215]. In the second part of this thesis, we will zoom out to consider the use of LCA in a broader context and provide perspectives regarding the environmental impacts of the IoT within environmental limits. To do so, we will build on the work carried out in this first chapters to draw the environmental perspectives on concrete examples.

PART II
Environmental perspectives for the IoT within environmental limits

5
Limits of LCA to assess environmental sustainability

If you really think that the environment is less important than the economy, try holding your breath while you count your money.
– McPherson

AFTER concluding Part I of this thesis, a predictable and more conventional approach would be to use the results of the previous chapters to conduct eco-design and propose alternative version(s) of these IoT solutions with better environmental performance. However, given the environmental context depicted in Chapter 1, we estimate that it is more relevant for the second part of this thesis to better understand the limits of systematic LCAs for IoT with respect to the bigger picture of environmental sustainability. By investigating how the consideration of environmental limits such as planetary boundaries or Paris Agreement targets could impede the development of the IoT, we therefore aim at providing environmental perspectives for the IoT in the Anthropocene to go beyond the mere application of systematic LCA and eco-design.

This chapter hence initiates these perspectives by adopting a critical perspective regarding the systematic use of LCA to unveil the limits of this methodology in assessing environmental sustainability. We use historical insights and existing literature [33, 48, 49, 50] as a basis to further question the choice of environmental *efficiency* metrics and fosters the link between relative and absolute environmental metrics.

The chapter is organized as follows. First, we provide historical insights regarding the development of LCA in the 1960's to ground perspectives in a socio-technological context. Then, we build upon existing scientific literature [33, 48, 49, 50] and investigate the environmental pitfall of focusing solely on improving relative environmental efficiency metrics. We illustrate this by putting the LCA results from Chapter 4 in perspective with planetary boundaries. We further explore the difference between relative and absolute environmental impacts with a simple model that highlights the link between affluence and technology improvements. Finally, we build on the work carried out in the first part of this thesis for the production of ICs in Chapter 3 and we carry out an historical analysis which illustrates the limits of relying exclusively technological improvements to decrease absolute environmental impacts.

5.1 Insights from LCA history

Historically, the core idea behind LCA has its early roots in the 1960's, driven by environmental degradation concerns and the limited access to resources in developed countries [215]. Life-cycle-oriented approaches hence emerged to develop methodologies and tools able to support the environmental profiling of products, mainly within companies at first. Pioneers sectors were chemistry, energy, and logistics. It took more than 30 years to diffuse outside of the industry and eventually penetrate the scientific community and the public sector, leading to the rapid development of several LCI databases and LCA software such as SimaPro and GaBi. Then, the increasing complexity of product systems and the inconsistencies between studies led to a consolidation of the methodologies, an harmonization of the methods, and the introduction of the ISO standards requested by the industry in the late 1990's [215]. Nevertheless, it is important to stress that "the LCA methodology was very young and rather immature while the ISO standardization process took place", as pointed out by [215]. This can explain why these standards mainly focused on the fundamental principles of LCA, whereas they provide very few details on specific methodological choices [215]. This was then improved by the European Commission through the ILCD initiative. The release of ecoinvent as the first general reference LCI database in the 2000's was also a considerable improvement.

Over the last 30 years, the LCA methodology has therefore witnessed intense development to improve the evaluation of environmental impacts for products, to tackle methodological gaps, and to broaden the scope of analysis with questions on the macro scale [215]. Nonetheless, this brief historical perspective on the evolution of LCA over more than 50 years highlights that this tool was rooted and developed in a socio-technical context where the quantification of environmental impacts was primarily used to *manage* the exploitation of resources and energy in the context of products development and supply chain management [51].

5.2 From relative to absolute environmental metrics

It is clear that LCA helps to improve the environmental performance of a given product by reducing its direct environmental effects, i.e., to do *better*. However, although it can help to evaluate whether the environmental performance are *good enough* in the context of global environmental limits, it is not sufficient as explained in [33, 51]. In fact, such a product-oriented analysis can hardly tell alone that *global* limits are not exceeded [33, 34]. Let us mention that this limitation is also explicitly stated in the ISO standard [16] dedicated to the LCA methodology.

5.2.1 Normalization factors in line with planetary boundaries

An interesting attempt to link the LCA methodology to planetary boundaries is proposed in [49] where the authors developed *carrying capacity* references for the normalization step of LCA. The concept of carrying capacity is defined by [49] as "the maximum sustained environmental intervention a natural system can withstand without experiencing negative changes in structure or functioning that are difficult or impossible to revert". This could therefore be understood as the boundary between global environmental sustainability and unsustainability [49]. By providing normalization factors for a wide range of midpoint impact categories, they made possible the translation of an LCA midpoint result to the corresponding occupied carrying capacity in person equivalents. This differs fundamentally from conventional normalization factors, which are not aware of planetary boundaries.

In order to illustrate this in the case of IoT, we apply this normalization step to the results of the LCA carried out in Chapter 4. The carrying-capacity normalization results are shown in the last column of Table 5.1. The values are obtained according to Eq. 1.3, where IS_c are the characterization results provided in Table 4.3, and NF_c the carrying-capacity reference situation provided in [49]. However, as the carrying-capacity-based references do not have the same units as the ReCiPe method for all categories, the normalization could only be directly carried out for GWP, land use, and freshwater ecotoxicity. The other values are extrapolated based on the ratios provided in [49] for the corresponding categories, or using the planetary boundaries per capita provided in [216]. With the planetary boundaries-aware reference situation, we observe significant increases in normalized results for the

Table 5.1 Example of carrying-capacity-based normalization based on the full-scope characterization results provided in Table 4.3.

Impact category	**Conventional** normalization	**Carrying-capacity-based** normalization⋆
Climate change†	0.21	1.67-3.15
Primary energy demand	-	-
Terrestrial ecotoxicity†	0.05	-
Terrestrial acidification†	0.05	(0.02)
Photochemical ozone formation†	0.10	(1.55)
Land use†	0.03	0.01
Human toxicity, non-cancer†	<0.01	(<0.01)
Human toxicity, cancer†	0.09	(0.01)
Freshwater eutrophication†	0.01	0.01
Freshwater ecotoxicity†	0.01	(<0.01)
Freshwater consumption†	0.05	(0.06)
Abiotic depletion potential (elements)‡	0.61•	1.14

† : ReCiPe 2016 v1.1 Midpoint (H) ‡ : CML2001 - Aug. 2016
⋆ : Carrying-capacity-based normalization results (typical), based on [49, 216]
Values in brackets were extrapolated by the authors of this thesis.
• : Normalization factor for 2000

GWP, the photochemical ozone formation, and the abiotic depletetion potential. These increases can be explained by the fact that the carrying-capacity normalization factors per person per year are smaller in the context of planetary boundaries, e.g., for GWP, 522-985[1] kgCO_2eq [49] rather than 7990.4 kgCO_2eq with the ReCiPe method. This is very similar to the results provided in [48].

The use of a *carrying-capacity*-based normalization is a useful step towards a stronger link between LCA and planetary boundaries. Yet, this approach does not modify the functional unit of the LCA, as it only changes the reference situation of the normalization step. It remains therefore product-centeric. In the rest of this chapter, we further investigate the link between relative and absolute environmental metrics to highlight that although LCA is a very useful tool to assess the environmental impacts of a product and support its eco-design, it is not sufficient to ensure absolute[2] environmental sustainability [33].

[1] These two normalization factors are given for a radiative forcing of 1 W/m^2 and a temperature increase of 2°C, respectively.

[2] Bjørn et al. define *absolute sustainability* as a state where carrying capacities are not exceeded, independently of any product or service definition [33].

5.2.2 The eco-efficiency pitfall

In ICT, a substantial portion of research and innovation efforts is focused on improving efficiency with respect to resource and energy usage [CP4]. Using LCA to support eco-design is somehow similar to existing optimization practices for key performance indicators (KPIs) [217][CP4], except that environmental indicators are used in eco-design rather than economic or technical performance metrics in conventional optimizations [95][JP2]. In other words, the LCA methodology can be used to improve the efficiency of technologies with respect to environmental impacts, often coined *eco-efficiency*. As pointed out by Hauschild et al. [51], this corresponds to the improvement of the technology factor in the IPAT equation (see Eq. 1.1). Nevertheless, the question whether the improvement of the last term T can be done independently from the other terms should be clarified, especially regarding the affluence. In this section, we present a very simple yet realistic model inspired by [218, 33] to depicts the coexistence of both absolute and relative environmental impacts, as illustrated in Fig. 5.1.

Figure 5.1(a) formulates the total annual environmental impacts $I_{tot}(t)$ as a linear function of the product throughput t, i.e., the number of (functional) products[3] fabricated (or deployed) per year,

$$I_{tot}(t) = \alpha t + \beta, \tag{5.1}$$

where α is the throughput sensitivity, i.e., the marginal environmental impact per product, and β the fixed environmental impacts. For a given reference throughput t_r, the environmental impact per product can be obtained by dividing the total environmental impacts by the product throughput. This corresponds to the eco-intensity (the inverse of the eco-efficiency),

$$I_{norm}(t_r) = \alpha + \frac{\beta}{t_r}, \tag{5.2}$$

which is the slope of the line between the reference situation R and the origin, as shown in Fig. 5.1. The throughput is likely to be upper-bounded by a maximal practical production (or deployment) capacity t_{max} and lower-bounded by a minimum sale level t_{min} that brings economic profitability. Additional considerations [51] including external factors such as price elasticity, market limitations or constraints (e.g., legal, economical, technical, or physical), and non-linearity effects are not included here to preserve the simplicity of the conceptual model. In the context of planetary boundaries and absolute environmental sustainability, a *ceiling* [219] could also be defined to set an upper bound on the acceptable total environmental impacts, as illustrated in Fig. 5.1(a) by $I_{tot,lim}$. However, the definition

[3] Product refers here to a broad list of goods and services that could range from integrated circuits, IoT devices, to data traffic.

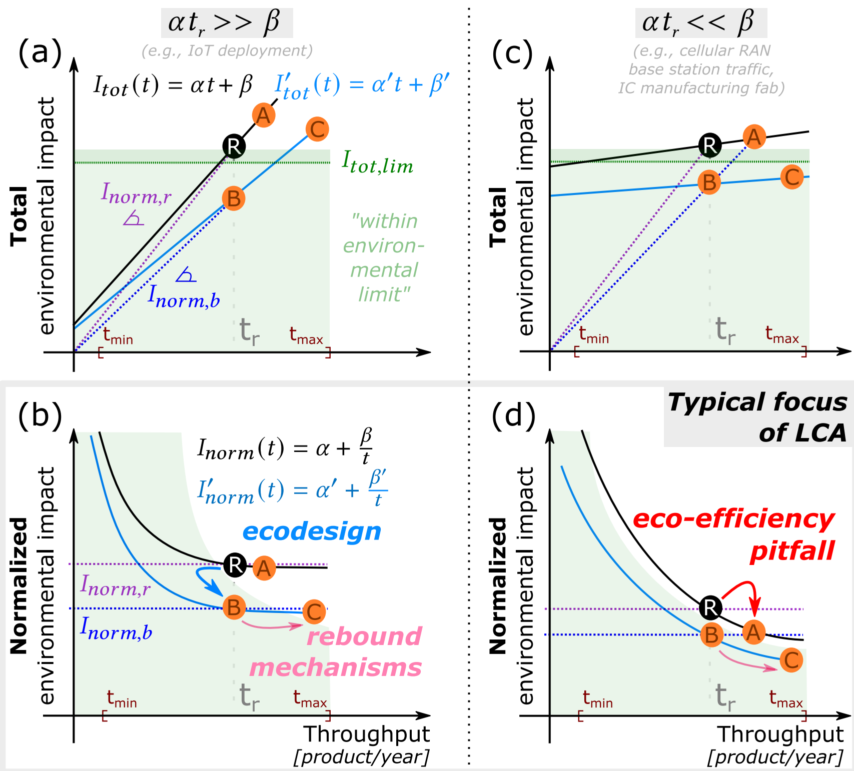

Fig. 5.1 Conceptual explanation of the eco-efficiency pitfall by considering the coexistence of (a) the total environmental impacts of a given production, and (b) the corresponding environmental impact normalized per product. Figure inspired by [218].

of this ceiling at the scale of a specific product implies complex arbitration and allocation between socio-economic actors and sectors, which is far from obvious but hopefully not impossible [33, 48].

Building upon the recent work initiated by Kiyotada Hayashi [218] in the field of LCA applied to agriculture, we use our conceptual model to point out the effect of alternative situations on both the absolute and relative environmental impacts, as shown in Fig. 5.1. This illustrates that a better eco-efficiency (i.e., a low eco-intensity) can be reached in situations A, B, and C although they are very different in nature. We define the *eco-efficiency pitfall* as the situation A in which the eco-intensity is improved through the increase in throughput, but results in higher total environmental impacts. Intuitively, this corresponds to the situation in which the fixed environmental impacts are amortized over a large number of products, as illustrated in Figs. 5.1(c)-(d) for $\alpha t_r << \beta$. The case $\alpha t_r >> \beta$ yields a different analysis as the eco-intensity tends towards a minimum limit equal to α for a very large throughput (mass production), therefore limiting the effect of increased throughput and suggesting that only eco-design can (significantly) improve the eco-intensity. The improved eco-intensity is reached for a throughput very similar to t_r in situation B thanks to eco-design, hence providing a reduction of the total environmental impacts as illustrated by $I'_{tot}(t_r) = \alpha' t_r + \beta'$. Nevertheless, even an eco-designed product can be subject to rebound mechanisms [86, 76, 220], which could reduce (or cancel out) the expected savings. This is captured by situation C in Figures 5.1(a)-(b).

Practical examples illustrating this conceptual simple model can be found in [105, 98, 95, 202, 221][JP2] and a very similar idea is described qualitatively in [48]. For instance, Figs. 5.1(c) and (d) would be useful in the case of high fixed environmental impacts ($\alpha t_r << \beta$), as observed for ICs manufacturing [95, 98] or cellular RAN base stations [202] if t is the total silicon area produced by a foundry or the total data traffic for the base station of a mobile operator, respectively. On the contrary, our case study in Chapter 4 would rather correspond to $\alpha t_r >> \beta$ in Figs. 5.1(a) and (b), because the fixed environmental impacts are small and the total environmental impacts strongly correlated with the number of products. If the throughput of IoT solutions deployed is kept the same, effective absolute environmental reductions can be expected which motivates to start eco-design. Nevertheless, if this eco-design optimization is used as a marketing argument to increase the number of deployed solutions for instance, this will drive an increase in throughput which could cancel out the environmental savings, as foreseen by rebound effects dynamics [76, 220].

Although the conceptual model proposed in Fig. 5.1 is simplistic, it provides more intuition regarding the link between relative and absolute environmental impacts. Furthermore, it could help discriminating between effective eco-design improvements and improvements obtained through increased throughput. In fact, although it is not trivial to predict rebound effects in the case of eco-design improvements, the effects of an increased nominal throughput can be anticipated and should not remain unreported neither seen as eco-design or environmental improvements. For this reason, we argue that comparison of relative efficiencies should be done at iso-throughput, or at least throughput should be clearly reported when comparing the eco-efficiency of several solutions.

5.3 Environmental implications of Moore's law

The previous considerations focused on quasi-static examples (short term), where the notion of time is only partially included. However, time has its importance in the context of climate change, as delaying GHG reduction today requires steeper reductions in the (near) future for respecting the corresponding planetary boundary. Therefore, analyzing the long-term evolution of the environmental intensity of technology over the years can help to identify the presence of environmental trends and better understand what we could expect from technology improvements in the mid- or short-term to compensate for increasing affluence and meet the required global reduction targets. In this context, we conduct a historical analysis of the evolution of the environmental impacts generated by the production of one cm^2 of IC since 1980, which we then put in perspective of the 1.5°C Paris Agreement target, assuming that production volume keeps increasing at the same rate. Before conducting the quantitative analysis, we provide a brief historical context regarding Moore's law, as it is undoubtedly one of the most iconic trend of exponential efficiency improvement in the field of ICT.

5.3.1 Historical context

Originally, Gordon E. Moore extrapolated the constant doubling of the number of transistors per wafer every one or two years[4], enabled by CMOS technology downscaling [166]. Although this law was initially based on empirical observations from electronic products of the 1960's, it quickly became a driver for technological innovation and hence shaped semiconductor roadmaps for decades [166, 223, 224, 167]. In fact, rather than being just a prediction, "it became an expectation and self-fulfilling prophecy [...] for engineers and companies that saw the benefits of Moore's law and did their best to keep it going, or else risk falling behind the competition", as stated by [225]. The word *law* has therefore nothing to do with a natural or inexorable phenomenon [222], as it is rather a forecast that turned into an industrial roadmap. In fact, Moore's law remains a reference for technological progress, despite concerns about a slowdown due to the fact that transistor dimensions are getting closer to the theoretical physical bound, i.e., the size of the silicon atom [225, 226][CP4]. A key element at the core of Moore's law was the joint consideration of technological performance and economics [225], which established a feasible and very attractive way to ensure economic profitably[5] of integrated circuits manufacturing for years to come [225, 167].

[4]Moore's original paper published in 1965 [166] mentioned a doubling every year for the next decade, but he revised his forecast in 1975 to a doubling every two years [167, 222].

[5]Gordon E. Moore himself claimed that "integrated circuits were going to be the route to significantly cheaper products" [167].

It is clear that environmental considerations have never been an objective of Moore's law, as it was totally disconnected from any environmental constraints when it has been formulated. Nevertheless, the environmental context has changed since the formulation of Moore's law and the environmental implications of this unrestrained technology development should now be discussed according to the challenges of *our* time [61], namely drastically reducing the global GHG emissions and the pressure of humanity on the Earth system *within the next decades*.

In 2021, we co-authored a study with Bol et al. [CP4] taking a first step in that direction. In fact, we used a hybrid IPAT/Kaya-like[6] decomposition to question whether the simple follow-up of exponential efficiency trend (including Moore's law) could help decreasing the direct GHG emissions of the ICT sector on a trajectory compatible with Paris Agreement. We foond out that the increase in affluence generally (over)compensates for the technology improvements, strongly suggesting the presence of rebound effects in ICT and the conflicting trends with Paris Agreement targets. Albeit this is an interesting attempt to investigate the effects of Moore's law on the overall carbon footprint of the semiconductor manufacturing sub-sector, that study lacked a fine-grained and comprehensive analysis based on industry data for the environmental footprint of IC production over a longer period of time (2004–2019 in the study).

5.3.2 Methodology

The present analysis therefore aims at filling that gap by using long-term perspectives[7] to analyze the evolution of environmental impacts per cm^2 for the IC production sub-sector, over several decades. Moreover, we propose to analyze the question in a slightly different way. We postulate that overall affluence keeps on increasing at the current rate, while we impose the rate of required CO_2 reduction on the global impacts to meet the 1.5°C Paris Agreement target. This hence provides an estimate for the required rate of eco-intensity reduction (i.e., the carbon footprint of producing one cm^2 of IC thanks to technology improvements), which we can then compare to historical trends to understand *to which extent this could be technically feasible in the mid- short-term*. In this context, we first extend the study conducted in Chapter 3 by gathering historical data reported for the period 1980–2010 and we use the same ten features to support the analysis and the identification of scope mismatch, as depicted in Table 5.2.

[6] The approach is very similar to the IPAT equation described in Eq. 1.1, and was also investigated in another recent study [227].

[7] This approach is inspired by P. Teehan's observation, highlighting that "researchers should move past snapshot views and consider longer-term trends in order to produce meaningful research with some longevity" [18].

Table 5.2 Streamlined classification of historical data sources considered in the study, according to the ten features defined in Table 3.1.

Features	(1)			(2)	(3)	(4)	(5)		(6)	(7)	(8)		(9)	(10)	
	Tech. type	*Front-end*	*Back-end*	**Tech. node (nm)**	**Wafer size (mm)**	**Yield**	**Infra.**	**Upstr. materials**	**Geogr. location**	**Indic. coverage**	**Process details**	**Transp. norm.**	**Assess. approach**	**Prim. data**	**Depend-encies**
(N=9) Scientific literature/Foundries															
Williams, EST (2002|1993-1999) [163]	mix	✓	⊖	⊖	150	⊖	✓†	✗†	GLO	PED◇;W	✗	✓	↓	✓	✗
Williams, EST (2002) [163]	M	✓	✓	⊖	200	✓	⊖	✓	GLO	PED◇	✓	✓	↑	✗	✓
Hu, ENERGY (2003|1999) [228]	⊖	✓	✗†	⊖	150;200	✗	✓†	✗†	TWN	PED◇	✗	✓	↓	✓	✗
Hu, ENERGY (2003|1983-1997) [228]	⊖	✓	✗†	⊖	⊖	✗	✓†	✗†	USA	PED◇	✗	✓	↓	✓	✗
Murphy, EST (2003|2001-2002) [98]	L	✓	✗	130	150;200	✓	✗	✗	USA	PED◇;GWP◇	✓	✗	↑	✓	✗
Plepys, Ph.D. (2004|1983-2003) [168]	mix	✓	✗†	mix	150;300	⊖	⊖	✗†	GLO	PED◇;W;GWP◇	✗	✓	↓	✓	✗
Krishnan, EST (2008) [104]	L	✓	✗	130	300	✓	✓	✓	USA	PED	✓	✓	⇅	✓	✗
Deng, ISEE (2008|1995-2005) [158]	L	✓	✗†	⊖	⊖	✓	✓†	✗†	GLO	PED◇;GWP◇	✗	✓	↓	✓	✗
Branham, Ph.D. (2008|2006-2007) [162]	L†	✓	✗	⊖	⊖	✗	✓	✗†	UK	PED◇;W;GWP◇	✓	✓	⇅	✓	✗
Yao, EST (2010|2001-2008) [229]	⊖	✓	✗	⊖	⊖	⊖	⊖	✗†	⊖	PED◇;GWP◇	✗	✓	↓	✓	✗
Deng, JCP (2011|1995-2006) [177]	mix	✓	✗†	⊖	⊖	✗	✓†	✗†	GLO	PED	✗	✓	↓	✓	✗
Ercan, ICT4S (2016|1995) [20]	mix	✓	⊖	⊖	⊖	✓	✓†	⊖	⊖	GWP;PED◇	✗	✓	⊖	✓	✗

GWP : Global warming potential PED : Primary energy demand W : Water

L : logic M : memory ⇔ : full coverage (PED;GWP;W) ↑ : bottom-up ↓ : top-down ⇅ : hybrid ⊖ : not available ✓ : included ✗: excluded

GLO : Global USA : United States of America CN : China TWN : Taiwan UK : United Kingdom

◇ : converted from the electrical consumption in kWh (PED: assuming a PEF of 2.5 | GWP : assuming an average carbon intensity of 0.475 $kgCO_2eq/kWh$)

† : implicit, deduced by the authors ‡ : direct communication with the authors ⋆ : not peer-reviewed (scientific literature only)

For most of the historical data, impact values were reported in the scientific literature, although they were directly coming from the foundries. Moreover, a transparent normalization (i.e., data provided directly in environmental impacts per cm^2 was often available whereas this was less frequently the case for the industrial sources published over the last ten years. Nevertheless, historical values are generally reported for electricity consumption and water only, which significantly complicates the historical evaluation of the carbon footprint as (i) electricity consumption is not the only source of GHG emissions, and (ii) the carbon intensity of electricity evolved since then. The share of electricity in the total fab energy consumption is assumed to be 83%, as deduced from Deng *et al.* data for a similar period [177]. Furthermore, we assume a global carbon intensity factor of 0.475 $kgCO_2eq/kWh$, which is close to the value considered by Teehan [18] for LCA studies before 2010. As scope 1 was never disclosed in historical data, we assume that scope 2 only accounts for about 67% of the total GHG emissions, which is the *current* median value for foundries that provide detailed data when reporting their carbon footprint evaluation in CSR reports. For the primary energy consumption, we also assumed a constant PEF of 2.5, as we focus on the improvements made by the foundries themselves and in order to remove the variation from historical results. Nevertheless, it has been pointed out that PEF value should be revised as it likely misrepresents the evolution of efficiency with respect to electricity generation and distribution [230]. Regarding water consumption, no distinction is made between the different types of water as no information was available. We use medians for the comparison, as it is more robust than the mean in the presence of extreme values and better captures the data in the case of asymmetric distribution. Finally, historical distributions are obtained by considering the same weight for all data, in coherence with what we did in Chapter 3. All data and assumptions are provided in the Appendix C.

5.3.3 Results and evidence of rebound effect

The results obtained for the historical data are provided in Fig. 5.2 (in gray), next to the results obtained in Chapter 3 (in red). The comparison of the data from the foundries over the period 1980–2010 and 2010–2020 reveals an important finding: environmental indicators normalized per cm^2 did not significantly decrease compared to historical values from 1980–2010, as shown in Figs. 5.2(a) to (c). In fact, Figs. 5.2(a) and (b) point out a decrease per cm^2 of about -26% for PED and -17% for GWP whereas Fig. 5.2(c) shows an increase of about +12% for the water consumption. Undeniably, the number of transistors fitted on the same area of silicon has tremendously increased since then, revealing the impressive technological progress in the field.

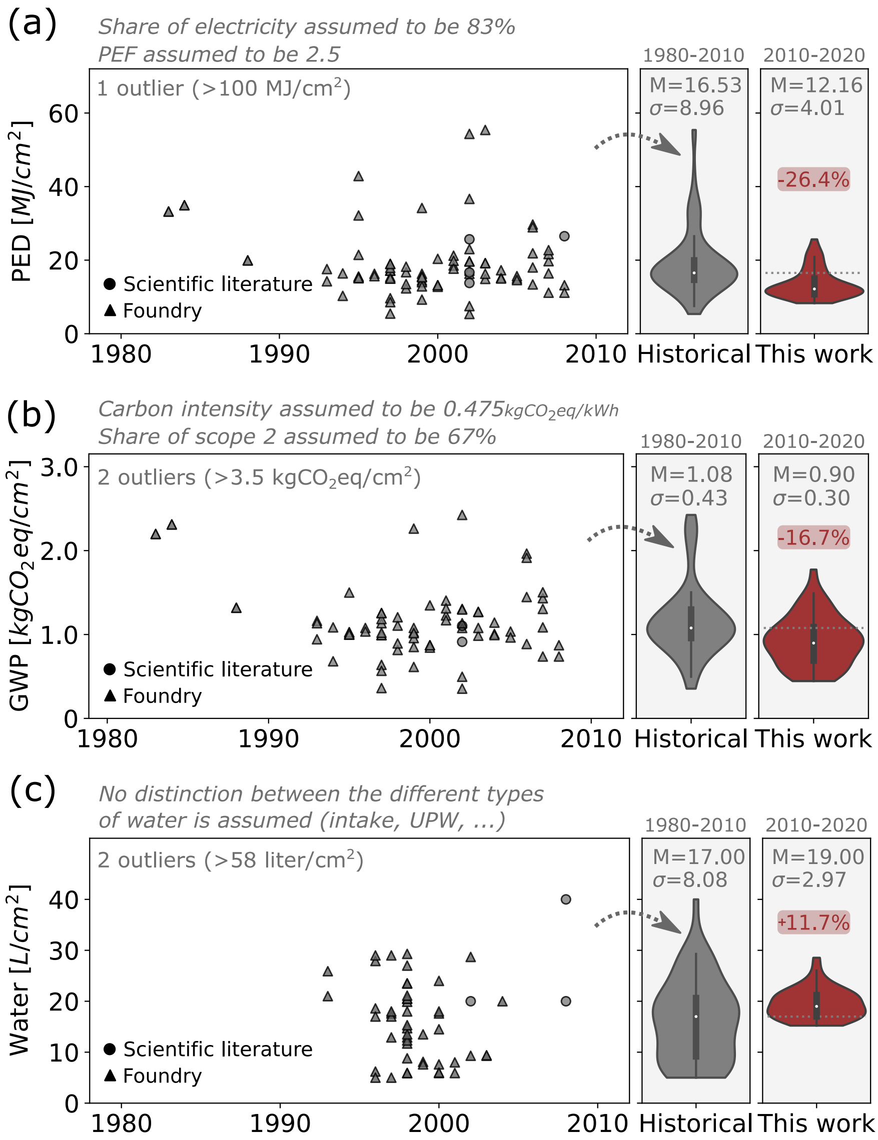

Fig. 5.2 Long-term perspectives between the results presented in this work (2010–2020) and historical data (1980–2010). The comparison per cm^2 is done only for data from foundries, with respect to (a) PED, (b) GWP, and (c) water consumption. Assumptions made by the authors are shown in italic. The median (M) and standard deviation (σ) are given in each case.

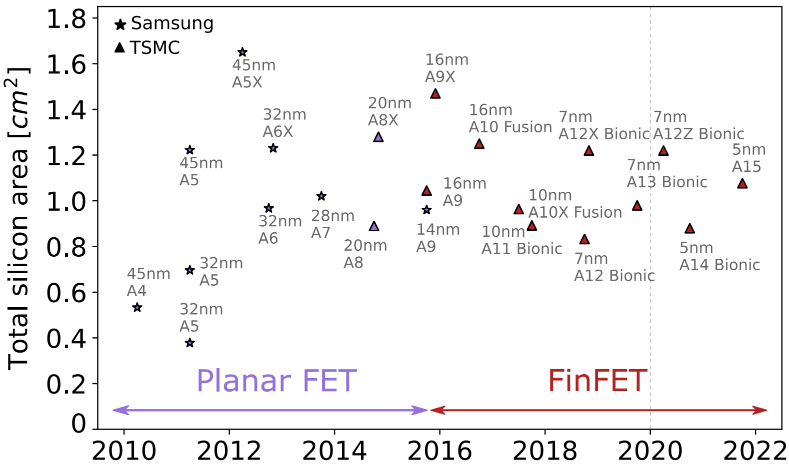

Fig. 5.3 Evolution of the average chip area of Apple's application processors.

Nevertheless, the computational demand, the constant increase of functionality, and the pervasiveness of electronic devices based on ICs also surged in the meantime [94, 158, 171], supported by the decreasing cost per transistor thanks to aggressive downscaling [166, 171, 225][CP4]. When analyzing the evolution of application processor chips from Apple over the last 10 years, Fig. 5.3 shows that the average die area is roughly constant even though the CMOS technology node shifted from 45 nm to 5 nm[8]. The increase in functionality can explain the almost constant die size despite technology downscaling [171].

The observation of the (roughly) constant die area for a given product is supported by others scientific studies over the last decades [100, 138, 158, 168, 171, 191, 228, 215]. More specifically, Kasulaitis et al. [138] observed a very similar phenomenon over the period 1999-2011 regarding the evolution of die area in the case of direct access memories (DRAM). They conclude that "despite significant technological improvement demonstrated by the rapidly decreasing size per function, consistent with Moore's law, the trend in total die area per DRAM card is roughly constant over time [...] suggesting a rebound effect by which dematerialization enabled by technological progress is being leveraged for increased functionality, not for a net reduction of material inputs". More than 10 years ago, Deng [158] already stressed the environmental consequences of this increase of functionality, which was first introduced by Plepys [168, 191] in 2004. In fact, he highlighted the issue of

[8] According to WikiChip, SemiAnalysis, and TechInsights, the silicon area for the recent 5nm M1 and M2 chips from Apple are about 120 and 140 mm^2, respectively.

ever increasing functionality as a reason for electronic devices to become more and more complex. Furthermore, he also made clear this trend was "likely to continue for as long as new functional features and higher performance is available", while pointing out that it was not due to a lack of effort from the industry to pursue efficiency but rather due to a fundamental dynamic for sectors seeing their processes and products evolving at the same time [158]. In general, these observations are further supported by Bjørn et al. [215], stressing out that "the level of services that we want from products and technologies is not static [...] we tend simply to expand our wants and expectations as soon as new possibilities evolve". This is even clearer for graphics processing unit (GPU) as the average die area is even increasing despite the aggressive technology downscaling [231]. Although GPUs may not be ubiquitous in every IoT device, they are considered and selectively used in certain IoT applications that require high-performance graphics, vision processing, or artificial intelligence capabilities within a constrained power budget [232, 233]. For instance, smart surveillance systems or autonomous drones may rely on GPUs for real-time video processing, compression, object detection, and analytics [233] and in smart home applications, they may be useful for speech recognition [233]. In practice, a representative example of available GPU-based hardware platforms for IoT applications is the NVIDIA's Jetson family [234]. Such advanced edge computing capabilities are clearly not required for all IoT devices, but this illustrates why a trend pushing towards embedding more computing capabilities on the edge devices may participate to a complexification of the devices and eventually, to an increase of the embodied impacts as the environmental impacts are proportional to the die size.

5.3.4 Perspectives with the 1.5°C Paris Agreement reduction pathway

In the context of the Paris Agreement, the UNEP estimates a reduction rate of 7.6%/year to meet the 1.5°C target [63], assuming a start in 2020. Therefore, if we assume that the total IC production volumes in terms of area keeps on increasing at the same rate as the last decade (i.e., +3.6–7.7%/year as shown in Fig. 3.6), the carbon footprint for producing one cm^2 of IC should therefore reduce by about 11-14% *every year*. This is far from the -17% observed over more than 15 years in Fig. 5.2(b). Indeed, this yields at best to -1.8%/year[9]. This is depicted in Fig. 5.4 where the best case scenario assumes the slower increase in total production volumes (captured by P·A in the IPAT equation) and the higher rate of carbon intensity improvements obtained through the historical data (captured by T). The worst case scenario assumes the opposite (i.e., higher growth in production volumes and slower carbon intensity improvements). These two scenarios lead respectively to

[9] If we consider that these improvements have been obtained over ten years, i.e., between 2005 and 2015 which is a very optimistic assumption. If we assume 20 years, this falls below -1%/year.

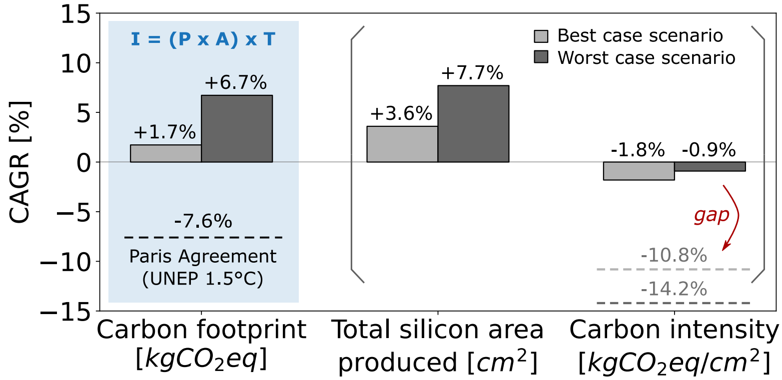

Fig. 5.4 Environmental perspectives based on the IPAT equation applied to the semiconductor sub-sector. Note that population (P) and affluence (A) are considered here as a single term (P·A), which captures the annual evolution of the total silicon area production worldwide.

+1.7% and +6.7%/year, which is far from the -7.6%/year estimated by the UNEP. Therefore, according to historical environmental trends, clear environmental concerns are to be expected if the IC production sub-sector keeps on increasing production volumes while committing to rapid reduction in GHG emissions. In addition, this will be further exacerbated if aggressive downscaling is pursued at the same time, according to the what we showed in Chapter 3.

5.3.5 Comparison with other studies

When we started working on the topic, we found no other study or report providing comparable analysis with respect to Paris Agreement reduction pathways. Similar conclusions can now be found in a recent white paper from imec [235], where they estimate that even with the use of renewable energy, the GHG emissions generated by chip production will be about 3× higher than the pathway it should follow to be in line with Paris Agreement reduction target in 2030. In an article published by McKinsey & Company [236] at the end of 2022, the conclusions are even more pessimistic as they claim that "implementing all known decarbonization measures will not get the semiconductor industry on a 1.5°C trajectory by 2030". A report issued by Greenpeace in April 2023 [237] also finds out that "zero semiconductor manufacturers analyzed in this report have issued climate commitments in line with the IPCC recommendations to limit global warming to 1.5°C". It is important to note that their study includes world's largest leaders such as Samsung Electronics, Intel, and TSMC. In addition, the Greenpeace report [237] points out that in 2021, about 84% of the semiconductor industry sourced its renewable energy through Renewable Energy Certificates (RECs). However, as the purchase of RECs does not add any new renewable energy to the grid, this hinder other sectors and other companies to behave similarly because the renewable energy supply is limited [237][CP4]. The semiconductor industry hence currently relies on one of the least impactful form of renewable energy sourcing to ensure its low-carbon energy transition [237].

These reports never directly mention or explore the possibility of including a non-technological lever such as capping or decreasing global IC production volumes to meet Paris Agreement pathways. It is most probably due to the fact that this would be in direct contradiction with economic growth, and therefore out of the scenarios considered in these studies. Despite its potential, such a paradigm shift would require a complete reboot of the current roadmaps, users behaviors, and business models in the electronics industry [OP1], which seems far from being on the current agenda. The next section hence analyzes industrial semiconductor roadmaps to better understand the definition and the evolution of environmental targets for the production of ICs.

5.3.6 Industrial semiconductor roadmaps and environmental targets

In this section, we analyze the ITRS/IRDS roadmaps published since the 2000's. More precisely, we focus on the Environment, Safety, and Health (ESH) section of the roadmaps. We consider editions from 2001, 2003, 2007 and 2015 as they all provide quantitative targets over at least four years ahead of the respective publication. Our analysis reveals a systematic target-relaxing phenomenon. Indeed, Figures 5.5(a) to (c) show that targets for energy consumption, water consumption and recycle/reuse rate are delayed or revised with relaxed targets at each new version of the roadmaps. For PED in Fig. 5.5(a), the final target almost matches the initial one but this is not the case anymore if EUV is used. For water, the final target is slightly higher than the one given in the 2001 ESH edition, as shown in Fig. 5.5(b). This is even more evident for the recycling/reuse rate in Fig. 5.5(c) where the target is significantly less ambitious than the one outlined in the 2001 ESH edition. Consequently, environmental indicators per cm^2 do not improve as fast as planned in the roadmaps published in the early 2000's. This analysis again points out the critical need for additional study [98] and for a transparent methodology. Indeed, very little information can be found in ITRS roadmaps regarding the methodology used to define their targets. As such targets are likely influenced by field-related constraints and business interests, more transparency is needed. In addition, the terminology often changes from one version to the other, which complicated the identification of targets over time. Again, a common framework to report targets and industry performance on a regular basis would greatly help in that matter.

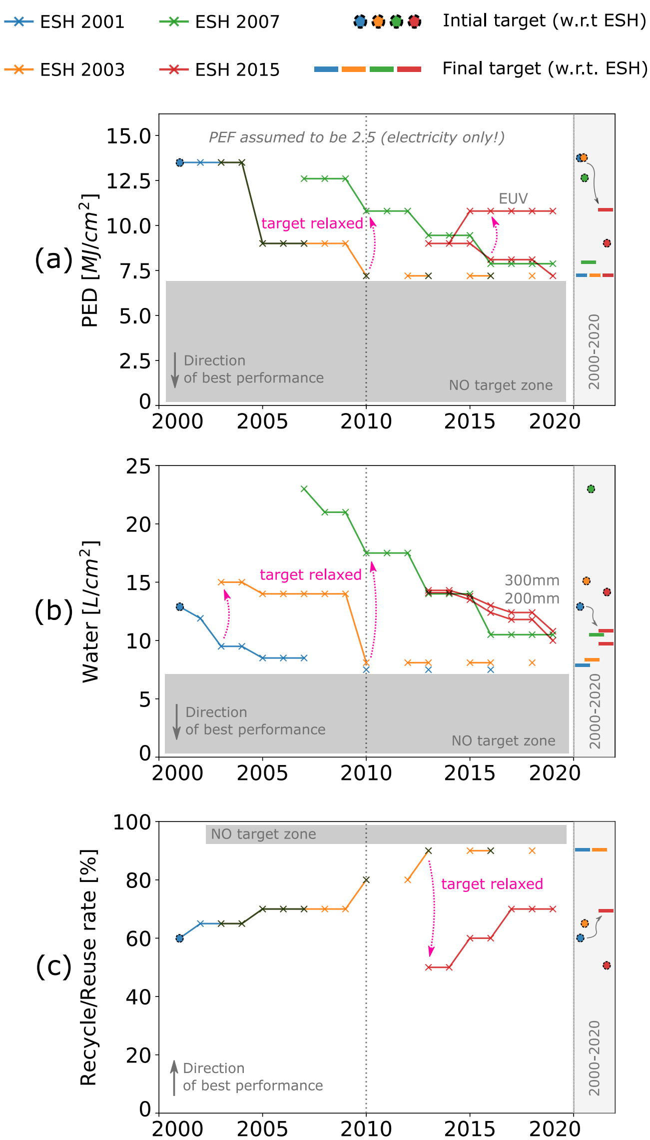

Fig. 5.5 Target-shifting phenomenon in ITRS roadmaps. The time-wise analysis of ITRS ESH/S roadmaps from 2001, 2003, 2007 and 2015 reveals that targets are systematically relaxed in the opposite direction of best performance in new roadmap versions. This can be seen for (a) total energy consumption (electricity only!), (b) total fab water consumption and (c) recycle/reuse rate. No target is available for total GHG emissions.

Regarding GHG emissions, it is striking not to find any quantitative target in ITRS roadmaps (as far as we could find reports). The only requirement regarding GHG exclusively focuses on fluorinated GHG (F-GHG), flurorinated heat transfer fluids and nitrous oxide for which the normalized emission rate is set to 0.22 $kgCO_2eq/cm^2$ for 2020 [185]. As F-GHG are only a part of the GHG emissions, this is far from being a sufficient and representative target. An explicit quantitative ITRS target is critically needed, especially when the ITRS itself points out in 2015 that "the combination of 450 mm, EUV exposure and rapid addition of new materials over the next 5 years pose significant challenges" [185]. The interactions between technology node, wafer size, yields and average die area were already introduced in [111, 168, 171], pointing out the difficulty to determine the environmental impacts associated with growing circuit complexity and increasing miniaturization trends. This again pleads in favor of long-term systematic analyses, especially because it also allows for a better detection of hotspots shifting or impacts transfer.

Finally, it is even more alarming to observe that after 2015, the lack of quantitative targets generalizes to all indicators in ITRS/IRDS roadmaps. This goes even further in the 2022 IRDS executive summary where it is clearly stated that "the ESH chapter was not updated for 2021 IRDS given the many changes that have occurred within the industry and externally, which require a fundamental reset in how ESH/S emerging challenges are addressed from a technology roadmap perspective" [238]. Historically, targets were provided even though they mentioned that the technology to reach them was not necessarily known. Today, the situation is even worse as the road ahead in terms of environmental targets is not even sketched. Let us stress out here that it must be seen as a strong alarm signal regarding the environmental sustainability of IC production, in particular because these roadmaps have been consulted more than 1 billion times[10].

5.3.7 Implications

We demonstrate that minimization of the environmental impacts per cm^2 will not be sufficient to quickly reduce the global absolute environmental footprint of the IC production sub-sector, especially for advanced nodes. Moreover, the trend towards more functionalities observed over the last decades reveals a clear rebound effect at the hardware level. This shows the limits of technology downscaling in being an effective solution for sustainability, as long as it feeds economic growth and fosters a rapid rise in the IC production volumes [171]. Therefore, we conclude that sobriety must be integrated into technological innovation and technology usage [239],

[10] This number was mentioned during the presentation "Chips Acts and IRDS building pillars and bridges over valleys of death" from Dr. Paolo A. Gargini, at the 2023 International Cooperation on Semiconductors (ICOS) workshop on Sustainable Electronics in Grenoble, France.

which calls for profoundly rethinking our socio-economic models and innovation roadmaps. As the need for sobriety in ICT was already pointed out about 20 years ago [168], we stress the urgency of the situation as a challenging question emerges: how should the IC production sub-sector adapt if global IC production volumes flatten or decrease in the long term?

This question is particularly appropriate given the current European Chips Act, which is aiming at relocating about 20% of the global IC production market in Europe by 2030 [240]. Both the USA and the European Union (EU) are currently massively investing to relocate the manufacturing of advanced manufacturing processes on their own soil [241], while committing at the same time to strong carbon reduction targets. With investments about 40+ billion Euros up to 2030 [240], it is clear that the EU expects the 2022 European Chips Act to eventually bridge the gap from lab to fab, including for advanced nodes. In fact, a key objective is to produce chips in European foundries in order to secure its electronics supply chain and boost its competitiveness through digitalization. This is further supported by the recent chip shortage [241] which revealed the increasing pressure on current production systems. Nevertheless, the Association for Computing Machinery (ACM) stressed the striking lack of environmental considerations in the European Chips Act, the important risk of rebound effects if technology is leveraged in pursuit of economic growth to the exclusion of environmental considerations, and the absence of consideration for the carbon emissions linked to the unrestrained growth of ICT activities [242]. It is therefore of critical interest to understand to which extent engaging into the relocalization of electronics manufacturing industry could impact the EU carbon reduction plans [JP4], especially if it focuses on the manufacturing of advanced semiconductor technologies [JP2]. Unfortunately, this is clearly not at the agenda of the European Chips Act, as it is completely eluding the question and fostering massive production of ICs in Europe. Unfortunately, such a disconnection between long-term goals and mid- or short-term planning will create steeper and high-risk decarbonization pathways, as stressed out in [237] although it was for the whole semiconductor industry.

5.4 Summary

In this chapter, we first gathered insights on the history of LCA to better understand the socio-technical context in which this tool has been (and is still) developed. This revealed that LCA is primarily a tool aiming at optimizing the eco-efficiency of products to manage the exploitation of environmental resources. We then built on existing literature [33, 215, 48] and argued that, although LCA is a very useful tool to assess the environmental impacts of a product and to support its eco-design, it is not sufficient to ensure absolute environmental sustainability. We proposed a simple conceptual model to clarify the link between technology improvement and affluence, which highlights the need to report throughput when comparing different relative environmental efficiency metrics. This further support the need to go beyond the exclusive focus on relative efficiency metrics and consider absolute metrics to foster perspectives with global limits [33, 48, 215]. Finally, we strengthen this observation with a historical macro-analysis of the environmental footprint of IC production. We reveal the environmental implications of Moore's law and the limits of CMOS technology downscaling in being an effective solution for environmental sustainability, if not combined with sobriety. Moreover, by analyzing the ITRS/IRDS semiconductor roadmaps since the 2000's, we pointed out the alarming lack of environmental targets for the upcoming years. As roadmaps are planning instruments aiming at linking shorter-term targets to long-term goals [62], it is very problematic not to find any explicit carbon roadmap to align actors and organizations in the semiconductor industry.

It is crucial for LCA practitioners and for people using the results of LCA to be aware that striving for an ever more eco-efficient product offers no guarantee to improve the global environmental situation. Given the current environmental context, it is critical to ensure that LCA is not used to legitimize a situation where incremental insufficient eco-efficiency improvements are targeted and reached [33]. This is especially important in the field of IoT mostly because of the wide variety of applications that are targeted, together with the variety of IoT solutions coexisting for each application [243][JP1].

6

Using futures studies to help keeping the IoT deployment within environmental limits

Perfection of means and confusion of goals seem –in my opinion– to characterize our age.
– Albert Einstein

ALTHOUGH the previous chapter already adopts a macroscopic approach to zoom out from the conventional product-centric vision applied in the field of ICT [27], it remains primarily focused on direct environmental effects. Clearly, systematically assessing the direct effects of IoT appears as an important first step, but more comprehensive approaches are needed to steer the environmental effects of the IoT within environmental limits, while taking advantage of its benefits where it can be relevant. Yet, the relevance of an IoT solution can hardly be estimated by focusing only on the technology itself, as it depends on several factors such as the socio-economic context and the policies in place for the territory equipped with this IoT solution. Addressing the multi-faceted environmental effects of IoT hence calls for holistic perspectives, as pointed out several times in the literature [51, 75, 73]. Even if this chapter is more of an exploratory nature, it also aims at understanding how the consideration of top-down global environmental limits can impede the (massive) deployment of IoT devices.

6 | Using futures studies to help keeping the IoT deployment within environmental limits

This last chapter aims at providing tangible suggestions and perspectives regarding useful approaches to be used (and further developed) in order to help keeping the IoT footprint within environmental limits. First, we aim at providing an estimate of the additional burden generated by the massive production of new IoT devices at the world scale. This is a useful contribution because current ICT carbon footprint estimates do not take into account the direct effects of IoT devices. Then, we address the challenge of identifying an approach to support the evaluation of the environmental relevance of IoT solutions with respect to environmental limits, while integrating direct, indirect, and structural environmental effects on the long term.

This chapter is structured as follows. First, we use the hardware profile framework developed in Chapter 2 to evaluate the carbon footprint of producing IoT devices for a massive worldwide deployment over the period 2018–2028. Several market forecasts are taken into account for the number of IoT devices, including projections issued by Statista and CISCO for instance. Then, we identify backcasting as a promising approach to be combined with LCA in order to identify IoT solutions that should be deployed, or conversely, the ones that should be discouraged for ecological reasons. We conduct a streamlined backcasting study on the case study of smart lighting in Belgium over the period 2020-2050, supported by the full LCA conducted in Chapter 4.

6.1 Estimating the carbon footprint of mass-producing IoT devices

In this section, we conduct a macroscopic analysis in order to forecast the worldwide carbon footprint of the massive production of IoT edge devices over a 10-year period (2018-2028), which is then put in perspective of the 1.5°C Paris Agreement GHG reduction pathway.

6.1.1 Methodology

We leverage the hardware-profiles framework presented in Chapter 2 to estimate the global carbon footprint associated with the massive production of IoT edge devices over a ten years period (2018-2028). This problem is complex and uncertain by nature as it depends on many parameters such as the number of devices, the diversity of the applications and designs, the user behavior, the improvement of technology through time and its level of adoption. A simplified modeling approach is hence proposed.

To account for the heterogeneity of IoT edge devices, we use our framework by creating two hardware profiles for simple and complex devices. Indeed, practical IoT deployment will be composed of many different hardware profiles and it would not be accurate to consider the same GWP for all devices. Simple devices are defined by the lowest value obtained in the framework and the carbon footprint resulting of the sum of all *HSL-0*. This yields a range D_s = 0.3-1.3 kgCO_2eq. Similarly, complex devices are defined by the highest value obtained in the framework and the carbon footprint resulting of the sum of all *HSL-3*. This yields a range D_c = 16.6-47.4 kgCO_2eq. Then, we propose three scenarios based on the share of IoT edge devices with a light hardware profile, denoted as α in our analysis ($0 < \alpha < 1$). Scenario 1 *deployment of simple devices* considers a majority of simple devices in the deployment i.e. $\alpha = 90\%$ of light hardware profiles. This scenario aims at capturing the case an IoT deployment based on small sensors with low functionality, similar to the occupancy sensor discussed in Chapter 2. Scenario 2 *balanced deployment* considers a balanced mix of simple and complex devices i.e. $\alpha = 50\%$. Finally, Scenario 3 *deployment of complex devices* considers a majority of complex devices i.e. $\alpha = 10\%$. The annual carbon footprint F_y for a given year y is therefore given by

$$F_y = N_y\big(\alpha D_s + (1-\alpha)D_c\big) \tag{6.1}$$

where N_y is the number of IoT devices deployed during the year y. Moreover, as we pointed out that the results obtained by our framework tend to underestimate the carbon footprint evaluation when compared to results from existing environmental reports due to the truncation error[1], we propose to compensate for this through the parameter ψ. Therefore, the annual carbon footprint with the framework revised upwards F_y^R is obtained as $F_y^R = \psi F_y$. We chose a value of $\psi = 2$, mainly based on the benchmarking conducted in Chapter 2. Regarding the number of devices, several trends exist [1, 2, 3, 4, 133, 244, 245, 246] as shown in Fig. 6.1(a-b). Among them, we consider only the ones from CISCO [3] and Statista [1] to model the massive deployment, as they seem to capture two main trends confirmed by the other sources. They do not include any traditional connected devices, e.g., computers, laptops, cell phones, smartphones, TVs or tablets. It is not always clearly defined if these trends account for gateways and if they consider all IoT edge devices. Additional details are available in Appendix E.

[1] Other potential sources are also pointed out in Chapter 2, but it is difficult to properly identify the source of discrepancies given the very low transparency of currently available environmental reports.

6.1.2 Forecasting results

Results for F_y and F_y^R with y ranging from 2018 to 2027 are presented in Fig. 6.1. This shows the importance to account at the same time for the exponential trends and for the diversity in hardware profiles in the upcoming IoT massive deployment. Shaded curves present the results if our framework is revised upwards by a factor $2\times$ to account for the truncation error. With a carbon footprint estimate ranging from 22 to 153 $MtCO_2eq$/year, it is not likely that the massive production of simple devices will raise serious concerns from a carbon footprint point of view. However, if the majority of IoT edge devices turn to complex devices, the conclusion can change with a carbon footprint estimate reaching 562 up to 1124 $MtCO_2eq$/year in 2027 worst-case scenarios. These scenarios imply that IoT edge devices embed increasing edge processing-memory abilities, wider user interfaces, bulky actuators and more advanced casings.

6.1.3 Limitations

First, we evaluated only the cradle-to-gate carbon footprint and left aside the carbon footprint generated in the other life-cycle phases. To have a comprehensive analysis, we should broaden the scope including the other phases of the life cycle. However, evaluating the use phase of all IoT devices will also be challenging due to the inherent high heterogeneity. One could also imagine an extended framework including *use-phase profiles*, even if this will strongly depends on the application, the programming, e.g., clock frequency, sleep modes, the hardware, etc. We did not investigate this, as focusing on the production aspects already pointed out environmental concerns but insights for further work could be found in [66, 145, 92].

Then, although this approach helps to move from a product-oriented analysis to macroscopic perspectives, it is mainly based on market trends and worldwide projections which are not anchored in any territory or tangible deployment policy. The actual relevance of these exponential trends predicting an ever increasing number of devices could indeed be questioned. For instance, saturation effects [66] may appear and curb the current trends. This prediction hence remains very general and theoretical. Albeit Fig. 6.1 provides a valuable temporal understanding rather than a punctual snapshot of environmental impacts, it implicitly requires to define the most probable future, which is particularly difficult with emerging technologies such as IoT. Moreover, we need to deal with an important uncertainty (note the log y-axis), which actually questions the relevance of reporting a precise estimate. This is a criticism that actually applies to most of the forecasts conducted for evaluating the carbon footprint of the ICT [30, 71, 204], although uncertainty is usually not clearly provided.

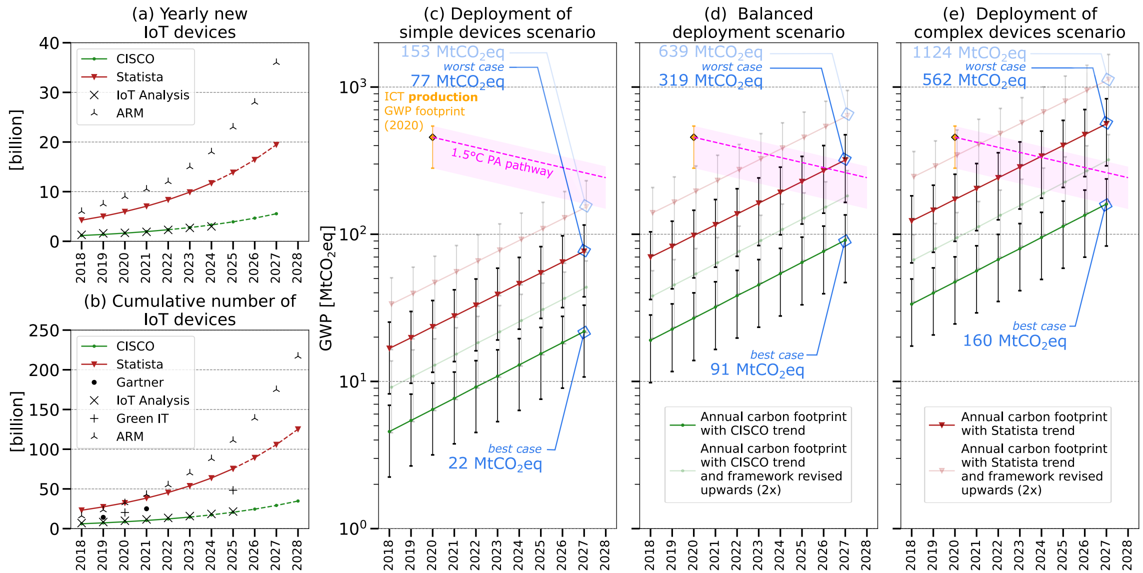

Fig. 6.1 (a) Yearly deployment of new IoT devices computed based on the trends in (b) which represents the cumulative number of IoT devices, according to most popular market studies and predictions. Dashed lines are personal extrapolation. (c-e) Macroscopic analysis of the *annual* carbon footprint generated by the production of IoT edge devices for different massive IoT deployment scenarios, based on (a). Shaded curves show the results if our framework is revised upwards by a factor 2× to account for the truncation error. (c) Scenario 1 *deployment of simple devices* considers a majority of simple devices in the deployment i.e. $\alpha = 90\%$ of light hardware profiles, (d) scenario 2 *balanced deployment* considers a balanced mix of simple and complex devices i.e. $\alpha = 50\%$, (e) scenario 3 *deployment of complex devices* considers a majority of complex devices i.e. $\alpha = 10\%$.

6.1.4 Comparison with other studies

To the best of our knowledge, only two studies carried out a macroscopic analysis of the carbon footprint generated by massive IoT deployment [71, 133]. On the one hand, [247, 71] concluded that the additional footprint due to IoT deployment only adds marginally to the overall carbon footprint of ICT, despite the large volumes of equipment and devices that could potentially be connected. They evaluates the total additional life cycle burden introduced by IoT devices at about 185-200 $MtCO_2eq$. However, they focused on a point estimate for a specific year (2015) which does not capture the exponential trends that characterize IoT massive deployment. They considered 27 billions connectivity modules for public displays, surveillance cameras, payment terminals, smart meters and wearables together with 500 billions tags and 1 billion small-cell wireless base stations. However, very few details about the modeling are available although it seems that the connectivity components were modeled based on the mobile connectivity devices for PCs [247].

On the other hand, the authors in [133] draw opposite conclusions and show an exponential growing footprint for manufacturing that reach up to 2000 $MtCO_2eq$ [2] in 2025. However, they considered annual energy increase per device for hardware manufacturing on top of the exponential trend for IoT deployment, which is an assumption that we did not make for our forecast. Indeed, more advanced technologies need more energy to be manufactured (as we showed in Chapter 3) but at the same time they can enable more integration. The evolution of the resulting carbon footprint over time is therefore uncertain [CP4] and this highlights the need to carry out LCA for IoT edge devices early in the design phase. We take a conservative assumption and consider that the average carbon footprint per product will not increase through time, although emerging trends like edge computing could push towards more complex hardware at the edge [248] in the upcoming years.

There was another evaluation[3] of the IoT footprint in the recent report issued by the ADEME/ARCEP [66] but the analysis is limited to France. The total carbon footprint of the ICT is evaluated at 17.2 $MtCO_2eq$ in 2020 and the study estimates the footprint in 2030 and 2050 close to 25 $MtCO_2eq$ and 49 $MtCO_2eq$, respectively. In the different scenarios, the carbon footprint of end-devices ends up being responsible for more than 75% of the total impact, among which 5-25% are attributed to the IoT devices.

---

[2] [26] did a conversion based on a global electricity mix of 0.63$MtCO_2eq$/TWh but a primary energy factor should be considered as [133] gives results in terms of primary energy. That study was also questioned by [26] because it is vastly overestimated compared to the study of Malmodin et al. [71]

[3] They used the concept of hardware profiles proposed in this thesis to model the impacts of the IoT.

6.1.5 Perspectives with the 1.5°C Paris Agreement reduction pathway

If the objectives of the Paris Agreement also apply to ICT, its carbon footprint should follow a pathway as displayed in Fig. 6.1(c-e), i.e., a reduction of GHG emissions by 7.6%/year starting in 2020 to be consistent with the 1.5°C target [63]. Given that the annual carbon footprint of ICT production in 2020 has been evaluated between 281 and 543 $MtCO_2eq$ [26], it should decrease down to 149–289 $MtCO_2eq$ in 2028. It clearly appears that the trends are conflicting as only the scenario *deployment of simple devices* seems to stand within limits, even though this will likely generate concerns after 2030 if massive deployment keeps up.

By providing one example of a GHG reduction pathway in line with the 1.5°C PA target on top of the forecasts, we support the analysis of trends rather than punctual estimates. We used a similar approach in [JP4] in the case of the carbon footprint of semiconductor manufacturing on the island of Taiwan, and Freitag et al. also introduced a similar approach in [26]. Our simple forecast demonstrates that even if the carbon footprint of individual IoT devices seems negligible when evaluated separately, the overall carbon footprint of a worldwide massive deployment of IoT devices can become problematic if the ICT sector aims at meeting the 1.5°C Paris Agreement target. This reinforces the need for systematic LCA of IoT devices to assess and improve their environmental footprint, but also shows that an unlimited growth of IoT devices is not compatible with the 1.5°C Paris Agreement targets.

6.2 Evaluating the environmental relevance of IoT solutions

Consequently, considering environmental sustainability in the context of the IoT does not only raise the question whether an IoT solution is *good enough* [51], but also the more sensitive question *whether a given IoT solution should be developed and deployed at all*. This triggers the difficult questions "how to identify IoT solutions to help keeping the IoT within environmental limits?" and "how to evaluate the relevance of an IoT solution with respect to environmental limits?".

The generally high expectations regarding the *favorable* effects of IoT (being economical, social, or environmental) fosters the development of a myriad of IoT solutions in several applications such as connected health, agriculture, cities management, and supply chain logisitics. As many of these IoT solutions co-exist in parallel, it is clear that focusing exclusively on the environmental improvement of individual solutions is not sufficient to foster environmental sustainability. In the worst case, we could even imagine that systematic LCA of IoT solutions could lead to worsening the current global environmental situation if it legitimates a growing proliferation of brand new *eco-designed solutions*, as the direct effects of all solutions would pile up at global. Nevertheless, considering only the direct effects of IoT would not provide a comprehensive picture of the IoT environmental effects. In fact, the previous chapters focused exclusively on the direct effects of IoT devices because the direct effects of IoT devices were vastly under-explored at the time we started working on the topic, but we left the indirect and structural effects of the IoT solution mostly unconsidered in this thesis.

In the following sections, we therefore consider these additional effects and we investigate **what approach can be used to identify IoT solutions that are relevant to be deployed, or conversely, the ones that should be avoided or strongly discouraged with respect to environmental limits**. Obviously, guaranteeing an absolute environmental sustainability is highly complex (if possible at all), regardless of the approach. Yet, even if the precedent forecasting identifies conflicting trends with Paris Agreement target, it does not answer the question "*how* to achieve this in practice?". The rest of this chapter therefore investigates *how* to plan for actionable future(s) of limits and/or scarcity that are "fundamentally different from the extrapolation of current trends" [61, 249].

6.2.1 Exploring different approaches

Given that the question we are addressing aims at fostering that environmental limits will not be exceeded in the future, it naturally falls within the field of future studies [250]. Working on future scenarios from a sustainability perspective is clearly a nontrivial task [91], mainly due to (i) the inherent uncertainty about the future, (ii) the challenge of agreeing on a single definition of (environmental) sustainability, and (iii) the difficulty to capture complex system dynamics. Prior to exploring different types of future studies, we first define the features that the approach should fulfill for our case study, namely:

- to be goal-oriented as we want to evaluate how to reach environmental targets;
- to integrate the quantitative data provided by the LCA results to model the direct environmental impacts;
- to allow for the integration of both direct and indirect effects of the IoT solutions [86, 89];
- to consider a period of time spanning at least the period between today and 2030 or 2050, i.e., at least 10-30 years;
- to capture spatio-temporal features specific to a given territory;
- to be at least suited to environmental analysis, if possible complemented with socio-economic considerations;
- to be able to cope with important uncertainties without compromising the relevance of the analysis.

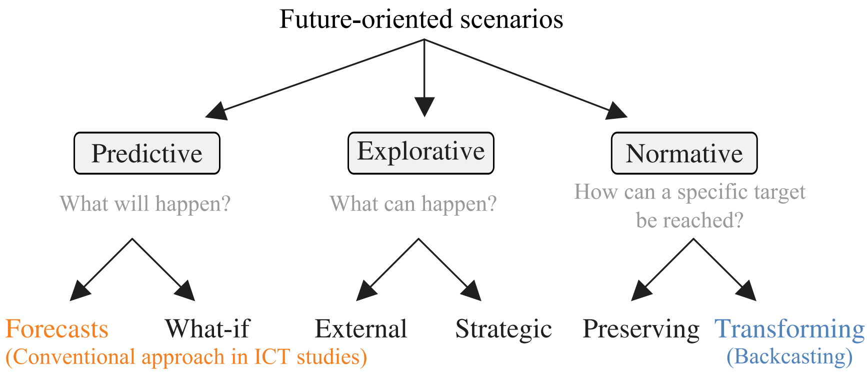

Fig. 6.2 Future studies and scenario typology, with the three main categories split in six types of scenarios. Figure adapted from [252, 251].

In the scientific literature, different tools and methods are proposed to carry out futures studies in a sustainability perspective [251]. Such studies are classified by [252] into three main categories, as illustrated in Fig. 6.2: predictive (forecasts and what-if scenarios), explorative (external and strategic scenarios), and normative (preserving or transforming scenarios). They respectively target the questions: "what will happen?", "what can happen?", and "how can a specific target be reached?" [251]. To address the first question (and to some extent the second), future-oriented LCA are pointed out[4] in the literature [51, 106, 251], although there is still ongoing debates in the LCA community on whether to use attributional or consequential LCA [105, 107]. In both cases, LCA is a quantitative tool that typically strives for accuracy and involves uncertainty analysis [251]. On the other hand, if the goal of the future study is to assess how a target can be reached (as formulated by the third question), normative scenarios should rather be used. In fact, they aim at considering a wider range of changes to the current situation (adjustments or profound changes) [251, 252], and quantitative tools are then useful to highlight the crucial factors needed to reach the target, to identify scenarios that would not be sufficient to reach the target, and to better communicate on the order of magnitude for the changes required. Consequently, there is no need to provide exact assessments nor to evaluate the scenario's likelihood anymore [251].

In our case, a direct approach could be to broaden the scope of the LCA to consider indirect effects in addition to the direct effects. This requires to change the functional unit to encompass not only the technological level (as it is typically

[4] In particular, De Camillis et al. [106] investigated for the Joint Research Centre (JRC) Institute for Environment and Sustainability (European Commission) the possibility to use LCA in future-oriented scenarios [251].

done in conventional LCA), but also the application level. Then, we should extend our LCA to be future-oriented and to fulfill the features defined above. However, even if it might be feasible *in theory*, this approach has several practical limitations First, it requires a solid expertise in the advanced modeling principles of consequential LCA [51]. This could be an important limitation if the approach has to be applied systematically, as even conventional LCA is far from being systematically conducted in the field of IoT [JP1]. Second, dynamic LCA should be used to capture the temporal evolution of the numerous model parameters. Third, the relevance of LCA results will be strongly affected by high uncertainties inherent to future scenarios. In addition to these three *technical* points, a major *methodological* limitation is that LCA is not a goal-oriented tool[5]. Therefore, we think that using exclusively the LCA methodology to address our question is not the best approach. Rather than solely relying on the LCA methodology, we propose to further investigate how LCA could be *combined* with other futures studies [251], as part of a broader environmental sustainability framework. Considering the set of features previously defined, the most suitable approach turns out to be the normative scenario in the transformative perspective given the long-term period and the nature of the changes introduced by the IoT solutions. This type of future study is also called *backcasting*, as introduced at the end of the twentieth century by John Robinson [253, 254].

6.2.2 Backcasting as a promising approach

Backcasting is intended for scenario analysis of changes occurring over 20 to 100 years in the future and involving many aspects of society, including technological innovations [255]. It is particularly well-suited to goal-oriented studies as it consists in defining a vision of a desirable future[6] and then working *backwards* from the end-point vision to the present [253, 256]. The key characteristic of backcasting compared to predictive forecasting techniques is to focus on *how* desirable future(s) can be attained, rather than predicting what futures are likely to happen [253, 255]. Although this difference may seem marginal at first sight, we argue that it is an important paradigm shift from the conventional forecasting approach used for ICT. In fact, similarly to what is pointed out in [249] and supported in [255, 257], backcasting could help us to "break away from default modes of thinking" and "think beyond established technological lock-ins and the path-dependence that follows from decisions that might have been taken decades ago". Given that it is very difficult to escape from a socio-technical lock-in situation once established [87], preventing new lock-ins from happening is critical. This point is particularly important in the field of ICT, as digitalization is already impacting almost all sectors of

[5]It can help to do *better* but it cannot evaluate if it is *good enough* with respect to environmental limits [33], as we supported in Chapter 5.

[6]Backcasting is hence explicitly normative [255].

our societies, hence creating a socio-technological lock-in [CP4]. Backcasts should hence help determining the physical feasibility of an alternative desired future and its implications in terms of policy measures to satisfy long-term targets [253, 258]. Backcasting is therefore inherently oriented towards decision making and strategic sustainability planning. Moreover, backcasting is particularly well-suited to address the complex nature of sustainability problems [255, 259] and particularly recommended when current trends are leading to an unfavorable future [258, 257], as it is the case in the Anthropocene.

The rest of this section is intended at illustrating the use and the potential of backcasting approaches in the literature. The grey and scientific literature have been considered[7] to identify studies and reports published over the last five years and using backcasting approaches. The keywords *backcasting*, *ICT*, and *IoT* where searched into Google Scholar for the scientific literature, and reports from the grey literature where identified mainly through Internet search, discussions with experts, and community workshops[8]. In total, thirteen studies are presented in Table 6.1 together with additional information and a brief description for each study. Although this is not an exhaustive literature review on backcasting studies[9], these examples already cover a variety of recent studies on the topic.

The analysis of the studies listed in Table 6.1 yields four key observations. First, it appears clearly that backcasting studies exist both in the grey and the scientific literature. Then, this shows that backcasting has been applied in several contexts and sectors, as also pointed out in [256, 260] for energy, forestry, chemistry, transportation, global GHG emissions, and agriculture for instance. More interestingly, Table 6.1 highlights that several recent backcasting studies have also considered ICT (or associated fields such as semiconductors, IoT, and smart cities for instance). Yet, this comes with two main limitations: (i) only a few studies are quantitative with a clear focus on science-based targets and these studies are generally from grey literature, and (ii) higher order effects are almost never considered, in both types of literature. Thirdly, the majority of studies which are defined as backcasting are based on several explicit steps, as defined by Robinson [253]. While several backcasting approaches and methodologies exist in the literature[10] and differ in their steps, they tend to share a very similar common ground [256, 260]. In particular, one very important part of the backcast is first the explicit definition and descrip-

[7] Only the literature written in English or French.

[8] ICT4S23 workshop on *Assessing the indirect effects of ICT – a review of some existing methodologies and frameworks and way forward, and the Sustainable ICT (SICT) doctoral summer school.*

[9] For example, a report from the Joint Research Centre (JRC) [259] provides several examples of specific backcasting initiatives in the 2000's to address the sustainability of mobility in Sweden, the United Kingdom, and even at a Europen level.

[10] For more details regarding the three main backcasting methodologies, please refer to [256] p.14-16.

tion of a common desirable future [258, 260], which is present in most studies from Table 6.1. Finally, Table 6.1 also highlights the high potential of backcasting for integrating interdisciplinary and transdisciplinary aspects in the multifaceted dimensions of sustainability.

A deeper analysis is carried out on three studies from Table 6.1 (in bold) to further highlight the potential of backcasting and LCA in the field of ICT. Among the scientific literature, an important number of studies have been issued by Bibri and colleagues on the topic of backcasting and smart sustainable cities [243, 256, 261, 262, 263, 264, 265]. They propose multiple qualitative case studies and point out the important reliance on IoT and ICT to take concrete actions and help reaching environmental targets in environmentally data-driven smart sustainable cities such as Stockholm and Barcelona [256, 263]. Although no quantitative backcasting is proposed to support these claims on the environmental relevance of IoT solutions, they spotlight the strong commitments and initiatives from these two European cities to move towards sustainable development strategies supported by the integration of data-driven solutions [263]. Nevertheless, the author explicitly mentions that their work and framework are "predicated on the assumption that big data technologies and their novel applications associated with the informational landscape of smart cities have great potential to improve and advance the design strategies and technology solutions pertaining to the physical landscape of sustainable cities in terms of their contribution to the environmental, economic, and social goals of sustainability" [256]. In another paper from the same author [262], it is argued that "the use of advanced ICT in sustainable cities constitutes an effective approach to decoupling the health of the city and the quality of life of citizens from the energy and material consumption (...)". However, it clearly appears in Table 6.1 that there is no considerations of the direct effects of the ICT (and IoT) solutions or the higher order effects of ICT (e.g., rebound effects). The main focus is on the enabling effects of ICT. This stresses out the distorted picture of the environmental effects of IoT and ICT in these studies. Yet, another paper from the same author [264] indirectly echoes this gap, stressing out that "while the smart city movement has created numerous initiatives globally, almost all of them have failed or lack adequate potential to generate sustainable urban future" [266]. They also enumerate the discrepancies between the concept of *smart* and *sustainable* cities, and the weak connection between those [261]. Based on the analysis of [266, 264], three key reasons are brought forward to explain this inadequacy, namely the current approaches to (smart) urban development are (i) technocentric and reductionist, (ii) encouraging fragmented cities rather than cohesive ecosystems, and (iii) informed by market analysis rather than ecological studies. We therefore argue that a quantitative backcasting should help to ground, question, and analyze the environmental relevance of deploying IoT solutions with respect to environmental targets, rather than assuming its benefits prior to the analysis.

The French agency ADEME recently addressed this gap in a study named *Transitions 2050*, as pointed out in Table 6.1. They have been working during about two years with more than one hundred collaborators, experts, and a scientific comity to carry out a backcasting[11] approach dedicated to support strategic planning in France. The main common long-term objective of the four scenarios proposed in their study is to reach carbon neutrality in 2050, as inspired by the IPCC 1.5°C Special Report. The four scenarios are based on profoundly different assumptions and narratives, ranging from sufficiency and frugality to techno-solutionism. Each scenario is anchored in a techno-socio-economic narrative which is then converted into quantitative assumptions, parameters and models in order to eventually propose quantitative pathways to reach the environmental objective in 2050. As part of their backcasting approach for the French situation, they include digital aspects and account for ICT (and IoT) devices, infrastructures, and use [66]. An LCA-based methodology is used to evaluate the environmental impacts and they use the hardware profile framework to take into account the environmental impacts of IoT. To the best of our knowledge, this is the most recent, detailed and interesting example of a backcasting approach including ICT (and IoT). Nonetheless, higher-order effects are not explicitly taken into account in the scenarios.

A third interesting example is the approach proposed by [260] where the authors provide a flexible framework, code-named BECE (backcasting and eco-design for the circular economy), to support the symbiotic relationship between the two approaches in the context of circular economy. In fact, the combination of top-down and bottom-up approaches is essential to foster a systemic view [260], which supports the use of both backcasting and LCA methods. For instance, they point out that "backcasting can facilitate the alignment of successive incremental eco-design improvements into viable development paths toward the development of circular and sustainable business models". Even if the BECE framework is mostly tailored to corporate decision making, it can still be an interesting starting point in other contexts.

Although a few examples are provided in Table 6.1, LCA modeling approach for backcasting scenario assessments has still a low maturity in practice, with a low level of endorsement or testing [106]. Even if this generally confirms that LCA and backcasting could be complementary, additional explorative work is clearly needed. The rest of this chapter hence further investigate in this direction by using the evaluation of the direct environmental effects of the IoT smart layer in a backcasting scenario applied to smart public lighting. The focus on smart public lighting is chosen due to the context of the LCA carried out in Chapter 4. The objective of the following section is therefore to provide a broader perspective on these LCA results and foster their integration in a broader framework.

[11] Often called *rétrospective* or *prospective* in French.

Table 6.1 Examples of backcasting studies published in the grey and scientific literature over the last five years. This is not an exhaustive literature review.

Source	Year	Field	Approach	Quantitative	Environmental targets	Direct env. effects incl.	Higher order effects incl.	Dimensions considered	Brief description (taken or adapted from the study)
Grey literature									
Greenpeace [237]	2023	Global ICT technology supply chain (incl. semiconductors)	Defined by the authors as forecasting	Yes (i)	(i) Commitments aligned with the IPCC. They also take into account SBTi targets.	Yes (ICT)	No (but increase of demand included)	Technology, economy (market share), and environment	"This report calculates the future emissions of semiconductor manufacturers as a factor of production levels and electricity consumption, and the looming difference between projected emissions cuts and existing sources of clean energy on the local energy grid used by existing semiconductor fabrication plants in these companies' operations." The report focuses on the Asian situation.
ADEME [66]	2022	ICT/Digital (incl. IoT)	Backcasting (prospective); presence of steps (incl. vision)	Yes (i)	(i) The four carbon-neutral scenarios defined by the ADEME in [267] are inspired by the IPCC report and aim at reaching carbon neutrality in 2050. They focus on the French situation only.	Yes (ICT)	No (but increase of demand included; rebound effects not considered in the quantitative figures but included in the narrative of the scenarios)	Technology (society, economy, and policy indirectly through the scenarios), and environment	The report focuses on the environmental impacts of digital technologies in France until 2030 and 2050, based on an attributional LCA approach. In this report, the digital is considered as a sector in itself, rather than as a part of other sectors (as it was the case in the ADEME Transitions 2050 report).
McKinsey [236]	2022	Semiconductors	Future studies (not defined as backcasting)	Yes (i)	(i) Reduction of min. 4.2%/year (starting in 2020), in line with SBTi for 1.5°C in the near term. For the long term (2050), they followed the International Energy Agency's Net-Zero Emissions by 2050 Scenario, in which "energy and industrial-process CO2 emissions fall by 95 percent between 2020 and 2050".	Yes (ICT)	No (but increase of demand included)	Technology and environment	The article proposes a "coherent, industry-wide roadmap that could be considered by semiconductor device makers seeking to achieve a 1.5°C trajectory by 2030 and net-zero emissions by 2050".

... (continue on the next page) ...

Table 6.1 Continued.

Source	Year	Field	Approach	Quantitative	Environmental targets	Direct env. effects incl.	Higher order effects incl.	Dimensions considered	Brief description (taken or adapted from the study)
					... *(continue from previous page)* ...				
ADEME [267]	2021	Generic (incl. digital)	Backcasting (retrospective, prospective); presence of steps (incl. vision)	Yes (i)	(i) The four carbon-neutral scenarios are inspired by the IPCC report and aim at reaching carbon neutrality in 2050. They focus on the French situation only.	Yes (ICT and application)	No (e.g., 'rebound' only mentioned once)	Society, economy, policy, technology, and environment	The report gathers technical, economical, and social knowledge to nurture debates on possible and desirable options to meet the French low-carbon national strategy. Each scenario is aligned with a narrative acknowledging its vision of the world, and the implications of the chosen trajectory to reach carbon neutrality.
Mission Innovation [268]	2019	Generic (incl. digital)	Not defined as backcasting	No	"The 1.5 °C Compatibility Pathfinder Framework (CPF) was developed in response to the IPCC's 1.5 °C special report."	Yes (ICT and application)	No (e.g., 'rebound' only mentioned once)	Technology, economy (business models), policy, and environment	"The report presents a 1.5°C means-ends framework as a heuristic tool for assessing the consistency of mitigation options with strategies for limiting warming to 1.5 °C. The framework is designed to support decision-making by different actors at multiple levels. The CPF makes transparent the causal links from strategies (the 'means') to emission reductions and other desirable objectives (the 'ends')."
					... *(continue on the next page)* ...				

Table 6.1 Continued.

Source	Year	Field	Approach	Quantitative	Environmental targets	Direct env. effects incl.	Higher order effects incl.	Dimensions considered	Brief description (taken or adapted from the study)
					... *(continue from previous page)* ...				
Scientific literature									
Ebolor [258]	2023	Smart cities	Backcasting; presence of steps (incl. vision)	No	No pathway aligned with absolute environmental targets.	Yes (application, partially)	No	Society, economy, technology, and environment	The paper proposes a literature review and some exploratory case studies to "envision how future cities can be backcasted with frugal innovation underpinning the sustainability pillars". The study assumes explicitly that "the place of technology is to ensure that smart cities are sustainable... through systems such as the IoT, Big Data, and AI into urban infrastructure".
Bibri [265]	2021	Smart sustainable cities (incl. IoT)	Backcasting; presence of steps	No	No pathway aligned with absolute environmental targets.	Yes (application, partially)	No	Society, economy, policy, technology, and environment	The paper " identifies, distills, and enumerates the key benefits, potentials, and opportunities of sustainable cities and smart cities with respect to the three dimensions of sustainability (...) The methodological framework applied in the futures study combines and integrates normative backcasting and descriptive case study as qualitative approaches".
Bibri et al. [263]	2020	Smart sustainable cities (incl. IoT)	Descriptive and illustrative case study	No	No pathway aligned with absolute environmental targets.	Yes (application, partially)	No	Society, economy, policy, technology, and environment	"This paper investigates the potential and role of data-driven smart solutions in improving and advancing environmental sustainability in the context of smart cities as well as sustainable cities under what can be labeled environmentally data-driven smart sustainable cities".
					... *(continue on the next page)* ...				

Table 6.1 Continued.

Source	**Year**	**Field**	Approach	**Quantitative**	**Environmental targets**	**Direct env. effects incl.**	**Higher order effects incl.**	**Dimensions considered**	**Brief description** (taken or adapted from the study)
					... *(continue from previous page)* ...				
Bibri [256]	2020	Smart sustainable cities (incl. IoT)	Backcasting; presence of steps	No	No pathway aligned with absolute environmental targets.	Yes (application, partially)	No	Society, economy, policy, technology, and environment	"This study aims to analyze, investigate, and develop a novel model for data-driven smart sustainable cities of the future as a form of transformative change towards sustainability". The study integrates "a set of principles underlying several normative backcasting approaches with descriptive case study design to devise a framework for strategic urban planning whose core objective is clarifying which city model is desired and working towards that goal".
Sisto et al. [269]	2020	Strategic planning in Universities	Backcasting; presence of steps (incl. vision)	No	No pathway aligned with absolute environmental targets.	No	No	Society, economy, and environment	The paper tests "the suitability of backcasting as a participatory approach to involve stakeholders in discussing the most effective actions to improve sustainability within universities' strategic plan."
Sisto et al. [270]	2018	Community-led local rural development planning	Backcasting; presence of steps (incl. vision)	No	No pathway aligned with absolute environmental targets.	No	No	Society, economy, and technology	This study aims at showing "the suitability of a participatory approach, namely backcasting, to the outline of the Local Action Plan of a specific Local Action Group". This is in line with the European Commission encouraging Community-Led Local Development approach delivered by Local Action Groups.
Mendoza et al. [260]	2017	Generic	Backcasting; presence of steps	No	No pathway aligned with absolute environmental targets.	No	No	Society, economy (business models), technology, and environment	The paper proposes a framework coupling backcasting and eco-design, mainly for companies. They argue that "backcasting and eco-design can be used as powerful symbiotic tools". They also highlight the importance of creating a multidisciplinary team and they critical need to build an overarching vision for the backcasting.

6.3 Streamlined backcasting for smart public lighting

In this section, we carry out a *streamlined backcast* based on scenarios from public reports and scientific literature to illustrate the potential of backcasting. However, we cannot perform a fully quantitative backcast due to lack of time to develop inter- and trans-disciplinary interactions with field players (i.e., operators, municipalities, etc) to provide specific and realistic information and key quantitative values. Hence, the results remain conceptual which means that we should not draw final conclusions on the relevance of IoT for this specific case study. In the following section, we illustrate the different steps of the backcasting methodology detailed in [253] and the kind of results that could be provided with this approach.

6.3.1 Modeling assumptions

Step 1: Determine objectives
The purpose of this analysis is to understand if and how the deployment of an IoT solution for smart public lighting could help to meet the Paris Agreement target of 1.5°C. This is somehow very similar to the *Carbon Law* approach followed in [61, 62], or to the procedure proposed in the technical recommendation L.1450 from the ITU (Part II) for defining a 2°C trajectory for the ICT sector [271]. Moreover, Robinson [253] explicitly mentioned environmental targets as a strong driver for backcasting, which further supported in [255, 257]. We focus on the Walloon Region (Wallonia) in Belgium at the horizon of 2050 to anchor the backcast in a well-defined spatio-temporal context. The use of national or sub-national scale for backcasting is aligned with recommendations provided in [106], as the spatial boundaries correspond to political jurisdictions [253].

Step 2: Specify goals, constraints and targets
The type of desirable future society envisioned for the backcast is chosen to be *a world in line with planetary boundaries in 2050 (and after)*. This is then narrowed down to *Wallonia in line with the Paris Agreement target of no more than 1.5°C by 2050* [63, 272]. Note that we could also have considered the 2°C target, or even the Plan Air Climat Energie (PACE) 2030 [273] issued by the Walloon Region. In any case, the question of how to allocate the global remaining carbon budget between activity sectors and between countries to comply with the Paris Agreement is non trivial and subject to important inequalities [33, 274]. In PACE 2030, local authorities allocated GHG reductions for each sector. For instance, the tertiary sector (relevant for the public lighting) has been assigned a reduction of 63% for 2030 compared to 2005 [273]. In comparison, observed reductions in this sector from 2005 to 2019 were estimated to only 11%.

Step 3: Describe the present system
The current public lighting system in Wallonia gathers more than 600 thousand streetlights [275], which is estimated to consume at least 130 GWh in 2019, or about 1% of the total electricity of Wallonia [276]. If we consider a carbon intensity of 0.19 $kgCO_2eq/kWh$ for the electricity [277], this yields about 25 $ktCO_2eq$ in 2019. Local authorities have already planned to replace all the halogen streetlights with energy-efficient LED lamps by 2030 in order to reduce the costs of public lighting [278]. The existence of this plan highlights the importance of focusing on a national or sub-national scale [106].

Step 4: Specify exogenous variables
Exogenous variables are variables that are not included within the backcast itself but that must be specified for the backcast to be carried out [253]. A concrete example would be the improvements regarding the carbon intensity of electricity production in Belgium. We do not consider modifications in the impact of economic growth and population growth in the backcast and we assume the socio-economic system to be stable under the period of study. This could be discussed, but we leave it outside of the scope of this backcast.

Step 5: Undertake the scenario analysis
Several scenarios are listed in Table 6.3 in order to show the diversity[12] of scenarios that could be investigated for backcasting. These scenarios aim at considering both technological and non-technological evolutions that can be implemented by a change in behavior or policy. For instance, due to the steep increase of energy prices during the end of 2022, several municipalities decided to shut down public lights at night to reduce the electricity consumption and hence the energy costs [279]. In futures of scarcity, we could therefore imagine a partial shutdown of streetlights in the long term in a non-technological *Shutdown* scenario, although this can generate other issues, e.g., in terms of safety. The *No action* scenario considers that the current lighting infrastructure will be kept, and we illustrate the effect of a modification in exogenous variables through a decarbonation of the energy mix. Then, we consider IoT *smart* scenarios that implement dynamic remote dimming of lights, which offers more flexibility and extra energy savings [280]. Dimming schemes reported in the literature enable power savings of 15 to 40% for the lights [280], and this could go up to 60% according to the vendor company of the IoT solution under study. *Smart w/o IoT effects* and *Smart w/ IoT direct effects* scenarios differ by the inclusion of the IoT direct effects whereas *Smart w/ IoT effects* integrates indirect effects, including rebound and structural effects. Indeed, as stated in [91], "taking into account all these effects extensively is extremely difficult (if not impossible)".

[12] Other scenarios could be developed in a complete backcasting study, based on generating techniques including workshops with stakeholders and experts, Delphi procedure, etc [252].

Table 6.3 Definition of the scenarios for the backcasting.

Scenario	Description	Comment
Baseline		
No action	Current infrastructure with an electricity mix decarbonization of 0.8%/year† [63]	No action
Replacement with LED	Linear replacement of all streetlights with energy-efficient LED lamps by 2030	Already planned
Non-technological		
Shutdown	Current infrastructure with shutdown during 40% of the night time from 2022 to 2050	Inspired by recent shutdown
Smart		
Smart w/o IoT effects	Dynamic remote dimming and predictive maintenance (smart lighting without IoT effects)	Technological (IoT)
Smart w/ IoT direct effects	Dynamic remote dimming and predictive maintenance (life-cycle impacts of IoT included)	Technological (IoT)
Smart w/ IoT effects	(Conceptual) Integration of indirect together with Smart w/ direct effects	Socio-technological (IoT)

◃ : the effect of electricity mix decarbonation (*exogenous variable*) is not taken into account in the other scenarios

6.3.2 Results

Step 6: Undertake the impact analysis

The conceptual results of the streamlined backcasting are presented in Figure 6.3. First, this highlights the importance of focusing on the cumulative emissions rather than on exclusively on the pathways. In fact, the cumulative nature of GHG emissions in the atmosphere yields remaining carbon budgets for +1.5°C and +2°C, as explained in IPCC reports [35, 272]. Then, although the replacement of the lightning infrastructure with energy-efficient LED lamps is effectively decreasing the GHG emissions, this is far from being sufficient to fulfill the Paris Agreement. Moreover, given the delay introduced by the deployment of a technology, the system inertia should be systematically taken into account in the context of climate change [34]. Indeed, the longer we wait for GHG reductions, the faster we will need to reduce our emissions [61]. The non-technological scenario shows that a partial shutdown of public lighting (40% of the time) has the advantage to quickly reduce GHG emissions. However, Fig. 6.3(b) shows that this falls short from meeting the target on the long term. The *Smart* scenarios depict important energy savings, which turns into significant GHG reductions. Yet even the *Smart* scenario without any effects of the IoT is close to exceed the carbon budget around 2050 despite it assumes a massive deployment starting in 2020, which is clearly optimistic. The second *Smart* scenario includes the results of the LCA conducted in Chapter 4 (with its uncertainty), hence increasing the carbon footprint. Finally, we conceptually illustrates a few *Smart* scenarios with direct and indirect effects that could be explored with a comprehensive and detailed backcast. These scenarios include, for example, rebound effects capturing an increase in the number of streetlights,

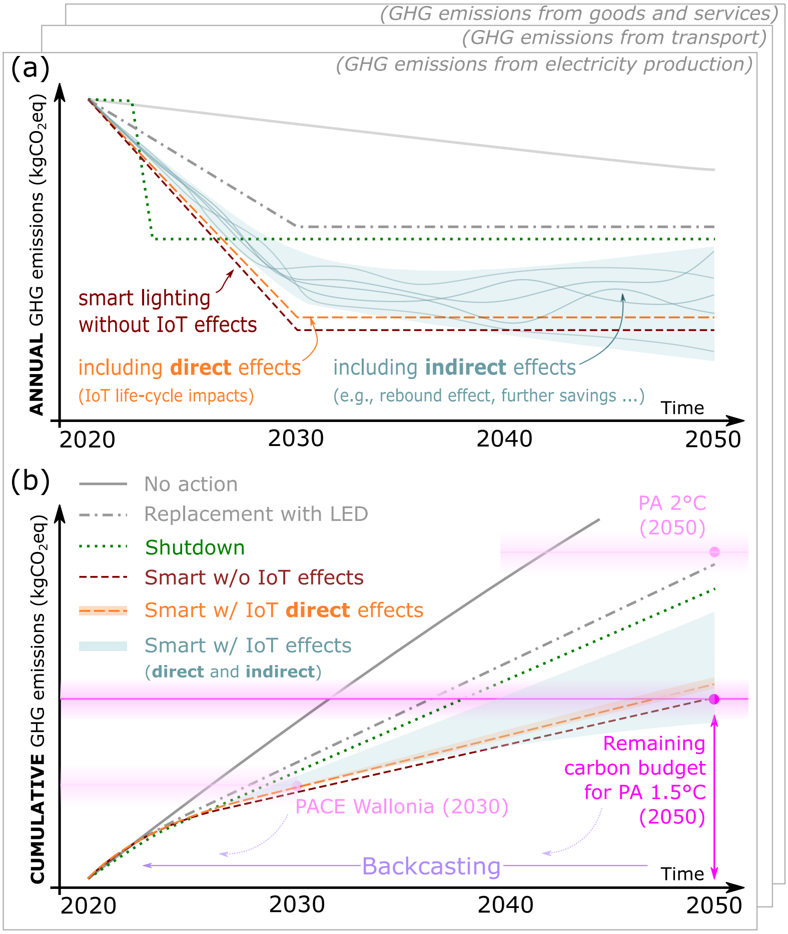

Fig. 6.3 Conceptual results of the streamlined backcasting study for (a) the annual GHG emissions, and (b) the cumulative GHG emissions. The backcast focuses only on the GHG emissions from electricity consumption in this case.

GHG emissions associated with the production of new streetlights, further energy savings enabled by advanced IoT solutions, etc. This shows that, in our case, no additional GHG emissions due to indirect effects are allowed if we want to reach the target set for 2050. Therefore, even if these effects are very difficult to accurately predict, we argue that backcasting can be used to identify scenarios that are largely insufficient and those that might be suitable options.

6.3.3 Discussion

First of all, our backcast only focuses on the carbon footprint as quantitative targets are explicitly defined at the horizon of 2050. It is hence important to remind that quantitative analysis tends to narrow down a complex problem to a small set of indicators capturing only a part of the overall problem [74, 87]. For instance, if deploying IoT solutions may help in some cases to mitigate GHG emissions, it will increase the consumption of abiotic resources [93] as we showed in Chapter 4 and increase the quantity of e-waste [6]. Moreover, our backcast focuses on the GHG emissions caused by electricity consumption, but the same approach should be carried out for the GHG emissions related to transport as the maintenance of the public lights undoubtedly entails a displacement of technicians and vehicles. Similarly, the impacts in other sectors should be considered as well, as suggested graphically by the portfolio in Figure 6.3.

A comprehensive backcasting would also include economical and social considerations in the underlying models and discuss more extensively what changes are needed to reach the target-fulfilling images of the future [252]. For instance, this could reveal the sensibility of a scenario or a pathway with respect to the context in which it was developed. As illustrated in [264] for the IoT, "[...] technologies might work in one sustainable city in a way that is different in another. Hence, they should sometimes be dramatically reworked to be applicable in the context where they are embedded". This shows the need for a systematic use of backcasting to account for local specificity and the limits of simply transposing backcasts in different technological, social, economical, and political contexts.

More generally, the need and relevance of quantitative scenarios could be questioned, especially because of the inherent uncertainty and several socio-economic factors affecting the study. Nevertheless, backcasting can be an effective way to systematically put reductions in perspective with global strategies and targets based on solid foundation from the environmental sciences, which was pointed out by Rasoldier et al. [91]. This distinguishes backcasting approaches from other ecological *cost-benefit-oriented analyses* such as *avoided emissions* approaches for instance [281, 282]. Furthermore, we argue that quantitative methods should be fostered in backcasting approaches, although this is rarely the case in the literature. Indeed, the main advantages of using quantitative backcasting approaches to deal with environmental limits [251] is (i) to help identifying the factors that are crucial to reach the target, (ii) to rapidly identify and discard scenarios and pathways that would not be radical enough to reach the target, and (iii) to better communicate on the order of magnitude for the changes required. This is especially important when it comes to GHG emissions reduction targets.

Nevertheless, the lack of suitable real-world data can be particularly problematic in the context of backcasting, as already pointed out in [253]. Regarding the evaluation of direct effects of IoT, streamlined analyses (e.g., based on hardware profiles for instance) could be used in the first iterations to decrease complexity and the associated time, at the cost of increased uncertainty. A similar idea is proposed in [260] although they remain generic. The importance of integrated research [283] to strengthen models and to better consider higher order effects (even with large uncertainty) therefore appears as a key element to conduct a comprehensive backcast. The backcasting approach can be seen as an opportunity to develop interfaces for inter- and transdisciplinary research while focusing on a concrete project [260]. Nonetheless, we argue that this should be further supported by interdisciplinary methods in practice. For instance, we suggest to investigate the use of causal loop diagrams [284] and *ilot de rationalité* [285] within this context.

Finally, even if forecasting and backcasting approaches might be complementary [257, 256], they are based on fundamentally different views on scientific explanation in the social sciences, as thoroughly explained by Dreborg [255] in the 1990's. Choosing between one approach or the other is not just a matter of convenience [255], as they are targeting different problems [255, 256] and come with fundamental discrepancies in their underlying theoretical foundations [255]. As of today, forecasting seems to be the dominant approach. Yet, given that the socio-technical system has to radically change to land *within* the planetary boundaries, this also suggests the need for important changes in the common and dominant practice of science.

6.4 Summary

In this last chapter, we zoomed out from the common product-oriented analysis to a broader approach to understand how the consideration of top-down global environmental limits could impact the ongoing IoT massive deployment of IoT devices. We first conducted a forecasting study to evaluate the overall carbon footprint generated by the production of IoT devices in the case of a a worldwide massive deployment. At the device level, this reinforced the need for systematic LCA of IoT devices to assess and improve their environmental footprint. However, at the macroscopic level, it clearly showed conflicting trends if the ICT is expected to meet the 1.5°C Paris Agreement target. More specifically, it showed that an exponential growth of IoT devices would not be sustainable because not compatible with environmental limits, therefore suggesting that not all IoT solutions should be deployed. Then, we showed that backcasting approaches have the potential to effectively help understanding *if*, and most importantly, *how* an IoT solution could help reaching GHG reduction pathways, contrary to traditional forecasting approaches in the field of ICT. We therefore argued that backcasting could be a realistic approach to "imagine and propose credible, preferable, and evocative alternatives" [249] in line with environmental limits. We illustrated this both with several recent examples from the literature and with a conceptual case study of smart public lighting in Wallonia, Belgium to put LCA results from Chapter 4 in the broader perspective of global environmental limits. While building upon already existing methodologies, this chapter illustrates the potential and the relevancy of combining streamlined LCA, full LCA, and backcasting approaches to help keeping the overall footprint of the IoT within environmental limits.

Conclusions

Never doubt that a small group of thoughtful, committed citizens can change the world; indeed, it's the only thing that ever has.
– Margaret Mead

THE rapid development of ICT over the last decades has deeply shaped our modern societies to a point where digitalization is now present almost everywhere. In particular, the IoT is the fastest-growing part of ICT in terms of number of devices, with market estimates projecting up to 200 billion connected *things* in 2030. However, the environmental impacts associated with this ongoing massive deployment are currently mostly overlooked, hence raising important environmental sustainability concerns exacerbated by the context of already exceeded planetary boundaries. In this thesis, we contribute to address this gap with two complementary approaches. The first approach consists in fostering the systematic bottom-up LCA of IoT devices by developing both streamlined and full LCA models to quantify the environmental impacts of IoT solutions. The second approach breaks away from the conventional strategy focusing on relative environmental improvements of individual IoT devices through eco-design and rather takes a top-down approach to consider global environmental limits such as planetary boundaries or Paris Agreement in the context of a massive IoT deployment. The rest of this concluding chapter gathers a brief summary of the main findings of this thesis, followed by a discussion of the known limitations, and suggestions for future research. Finally, recommendations are formulated, together with final thoughts on the roles of IoT in the Anthropocene.

O.1 Specific findings

Main conclusions from Chapters 2, 3, 4, 5, and 6 are summarized below in regards of the central research question of this thesis, namely *"to which extent could the systematic LCA of IoT devices help keeping the IoT footprint within environmental limits?"*. The graphical overviews shown in Fig. O.1 and Fig. O.2 depict how the different chapters are organized in this thesis.

Chapter 2

In this first contribution chapter, we propose the first quantitative framework specifically for streamlining the carbon footprint evaluation of the production of a wide range of IoT devices under consistent scope. We developed and benchmarked this framework while preserving a high level of details regarding the hardware of IoT devices. More importantly, we demonstrated the usefulness of using *hardware profiles* for the IoT and we showed that large inaccuracies (by a factor greater than 150×) can arise if the inherent heterogeneous nature of IoT is not considered (from simple to complex devices). This is a major finding, which effectively fosters environmental considerations in the field of IoT.

Chapter 3

Then, we further dig into the environmental impacts of key building blocks for ICT and IoT devices: integrated circuits. By conducting the first extensive literature review on the environmental footprint of IC production, we improved the current understanding of environmental impacts for these important components in ICT products and more specifically IoT products. Based on this review, we conducted unique in-depth qualitative and quantitative analyses, which confirm that technology downscaling increases the environmental impacts per cm^2 despite the variation introduced by the mismatch of scopes between existing sources. Three important progresses brought by our approach are that (i) we went well beyond the existing scientific literature by including four different literature categories, i.e., foundry reports, semiconductor industry roadmaps, scientific literature, and commercial state-of-the-art LCA databases, (ii) we included three environmental indicators, i.e., energy consumption, carbon footprint, and water consumption, and (iii) we introduced a list of key features to improve the standardization and comparison of future LCA studies on the environmental footprint of ICs.

Chapter 4

To conclude the first part of this thesis, we carried out a detailed full-scope multi-indicator LCA of a real-life IoT solution for smart public lighting, which is *per se* valuable given the current lack of detailed LCA for IoT solutions. We then compared the results obtained with a streamlined carbon footprint assessment based

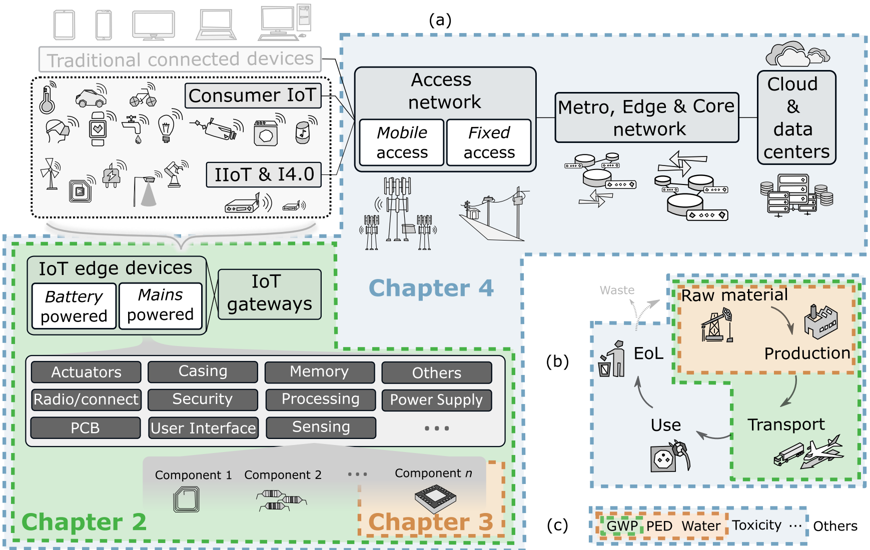

Fig. O.1 Graphical overview illustrating the links between the scopes of the three chapters for the first part of the thesis. (a) Schematic IoT network representation illustrating the different levels of abstraction in IoT systems. (b) Life-cycle phases. (c) Environmental impact categories.

on the hardware profile framework and showed the trade-off between the uncertainty reduction of the LCA results and the efforts devoted to it. Moreover, we highlighted the synergistic combination of streamlined and full LCA to foster the systematic LCA of IoT devices. In particular, we argued that although it is very useful and convenient to use streamlined LCA for a first evaluation (e.g., for strategic decision making), it must not substitute to full LCA.

Chapter 5

The second part of this thesis starts by pointing out that the mere and systematic application of LCA will not be sufficient to keep the IoT footprint within environmental limits if it focuses solely on improving the environmental performance of IoT devices. With a simple conceptual model, we clarified the link between eco-efficiency improvements and technology affluence, which points out the need to compare relative environmental efficiency metrics at iso-throughput, or to focus on global absolute environmental impacts rather than on relative improvements. As an example, we found out that the optimization of the carbon footprint of the production of one cm^2 of IC will not be sufficient to meet Paris Agreement target for the IC manufacturing sub-sector, if it keeps up with its current growth in produc-

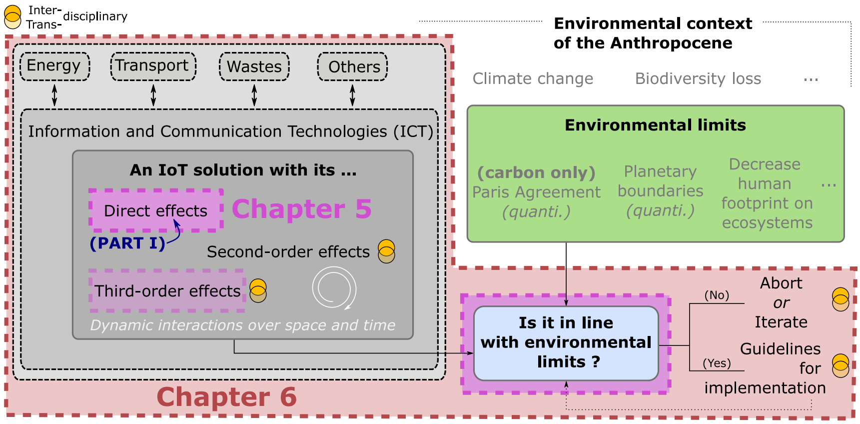

Fig. O.2 Graphical overview illustrating how Part I connects with the second part, and the links between the two chapters of Part II.

tion volumes. This showed the importance of historical trends to better understand the limits of technological improvements in decreasing absolute environmental impacts. More generally, our findings call for an urgent rethinking of technology roadmaps that currently foster mass production growth.

Chapter 6

Finally, we showed that the exponential growth of IoT devices will lead to foreseeable conflicting trends between carbon footprint of ICTs and Paris Agreement GHG reduction pathways. Consequently, we argued that if the number of IoT devices is to be limited for ecological reasons, an approach is needed to identify IoT solutions that are relevant to be deployed, or conversely, the ones that should be avoided or strongly discouraged with respect to environmental limits. By exploring the field of futures studies, we showed that backcasting approaches have the potential to help understanding *if* and *how* an IoT solution could help reaching environmental targets in other economic sectors. This synergistic combination of backcasting and LCA (streamlined and full) approaches can be seen as a paradigm shift from conventional forecasting approaches in the field of ICT, in particular because it is goal-oriented and more resilient to uncertainties by design. In practice, streamlined LCA could be used in the first iterations of the backcast, and then refined with full LCA (and eco-design) in a second time. Rather than fostering technology-push innovation, we argue that this approach has the potential to stimulate more socio-technical innovation in line with global environmental limits, as defined by the planetary boundaries or the Paris Agreement.

O.2 Limitations

We discuss below the known limitations of this thesis.

Methods

A significant truncation error was pointed out in the Chapter 2. Although similar observation were made in [18], it is difficult to further understand the origin of the differences as no details are provided in the public reports issued by major companies such as Apple and Google. Nonetheless, we stress out that this should also be reported in studies that make use of the framework, even if this complicates the interpretation of their results. Moreover, we argue that a range of values should be used for the streamlined carbon footprint evaluations, rather than a precise value.

The end of life of IoT devices

An important focus was made on the production phase of IoT devices, mainly because it was vastly under-explored at the time we started working on the topic. Nevertheless, the end-of-life phase is even less explored, although it can potentially hide important impacts. This may influence current hotspots for LCA of electronics, especially in terms of ecotoxicity and effective recycling methods in comparison to ideal scenarios. The lack of representative data about end-of-life impacts explains partially why the vast majority of LCA discard this phase of the life cycle. Moreover, the additional contribution of IoT to wastes from electrical and electronic equipment (WEEE) was stressed out in a white paper [6] issued by the ITU in 2020. They point out that WEEE from households and individual consumers is growing faster than infrastructure equipment waste mainly because of the growing number of individual devices, lifespans shortening and large amount of small hardware equipment used for the IoT. *Small equipment* and *small IT and telecommunication equipment* represent respectively 32% and 9% of the WEEE mass flow in 2019 [211]. As IoT edge devices will eventually become WEEE, end-of-life considerations should be addressed when discussing the impacts of IoT [6, 28, 29]. Let us mention that we did not consider recycling or lifetime extension scenarios of IoT devices in this thesis although the benefits of such approaches may also help to keep the IoT footprint within environmental limits.

Uncertainties

Although the presence of uncertainties is well known in the LCA community, very few ICT studies have properly addressed this concern in a comprehensive way so far, and this work is no exception to this shortcoming. Indeed, only a very limited subset of uncertainties sources presented in Chapter 1 have been explicitly addressed. In particular, we briefly addressed parameter uncertainty and model structure uncertainty in the first part of the thesis, while we touch upon scenario uncertainty and variability in the second part. For instance, although all our lifecycle models were implemented with a very similar setup (which ensures consistency), we did not compare the results that would have been obtained with other software or databases, and we did not investigate the variation introduced by different LCIA methods,e.g., ILCD, EF3.0, etc. Moreover, we argue that more advanced uncertainty analyses and sensitivity analyses should be conducted, e.g., Monte Carlo analysis and systematic sensitivity analysis. Finally, we believe that LCA of ICT would greatly benefit from practitioners explicitly addressing epistemological uncertainty, mistakes, and relevance uncertainty, which are usually not addressed albeit this research field is still in its early phase.

Databases and tools

We used Sphera LCA, a proprietary LCA software and proprietary electronic databases throughout the whole thesis. Although this is the case for the majority of studies, this significantly hinders the transparency and reuse of models and results. We argue that it is an important barrier for the systematic use of LCA in the field of IoT. Nevertheless, we fostered transparency as far as possible and provided as much supplementary material as allowed by the databases and the company sharing sensitive information.

Global sustainability

This thesis focused almost exclusively on environmental impacts. Nevertheless, socio-economical considerations should be included as they play an important role in the field of IoT, e.g., economical costs can define the level of maintenance, the inherent value of data provided by the IoT devices, the inequalities between the people who benefits from IoT business and the use of IoT solutions on one side, and on the other hand the ones impacted by resource extraction, e-waste management, increasing security risks [70], etc.

O.3 Future research

Based on the aforementioned limitations and based on gaps identified during the realization of this thesis, we propose some concrete ideas for future research.

Bill of material

The comparison we carried out between streamlined and full LCA pointed out the importance of having precise bill of material available, regardless of the approach. However, this is generally not the case for the majority of IoT (or ICT) products. Unfortunately, such information are very difficult to obtain if not directly provided. Reconstructing a full bill of material is a very time-consuming (and tedious) process, but it is a necessary basis to further conduct environmental assessment (at least according to the current methodology). Working towards a systematic method to collect and generate precise bills of material with a limited time investment could be an important step towards the implementation of systematic LCA for the IoT. The next step will be to improve the conversion step between the bill of material and the available database entries. This includes the systematic evaluation of key parameters such as silicon die area, technology node, PCB layers, etc.

End-of-life of ICT and IoT devices

Urgent work is needed to significantly improve the end-of-life modeling of electronics, as it will also impact the direct effects of IoT solutions. In fact, the current knowledge, databases, and models for the end of life are very scarce and only scratching the surface of actual environmental issues. Regarding the consideration of lifetime extension strategies for the IoT, the mutualization or the reuse of physical IoT devices might be considered in future work to limit the number of IoT devices to be deployed. Nonetheless, this might also influence the complexity of the devices, if they have to implement more functionalities.

Classification of IoT devices and allocation for the ICT sector

Because of the multiple definitions of the IoT, defining the scope of a LCA (or allocating the impacts) can turn out to be problematic in practice, as suggested in the last chapter. Indeed, IoT solutions may have multiple functions and be at the core of the functionality of the objects, or just extend the primary function of the object. Standardizing the classification of IoT devices and the allocation rules for the ICT sector is urgently needed[13].

Backcasting approach and future-oriented LCA

The backcasting approach is known to be well-suited to inter- and transdisciplinary research [255]. Synergies with social sciences, philosophy, and environmental economics could therefore be expected, together with interactions with policy makers and citizen for instance. Backcasting studies may combine the advantages of quantitative analyses with necessary qualitative considerations. Further research should investigate how to improve LCA methodology and models in the context of backcasting scenarios, including the use of consequential LCA.

Open-source LCA models

Future research is needed in the field of open-source LCA (e.g., OpenLCA and Brightway), as it is one of the biggest barrier to implement complex models that could be challenged, shared, improved, and established by the community. As pointed out by P. Teehan [18], "it is unrealistic to expect researchers and analysts

[13]The French agencies ADEME and ARCEP are currently working in this direction.

to start from scratch every time". Albeit open-source models would still be limited by databases that are mainly proprietary, this would already by an important step forward. Nonetheless, important changes are taking place in the LCA ecosystem at the moment, which may pave the way for more robust life-cycle models. For instance, the imec.netzero initiative recently developed by imec proposes aggregated open-source data on the environmental footprint of IC production for advanced technology nodes [286].

O.4 Recommendations

The recommendations provided below are not only of interest for the scientific community, but also for workings groups on industrial roadmaps, universities, and decision-makers in the field of ICT.

Industrial semiconductor roadmaps

A common framework to report data on the environmental footprint of IC production should be implemented in the near future. In particular, it should foster the analysis of environmental trends and the comparison with targets issued in industrial semiconductor roadmaps. Industrial semiconductor roadmaps should systematically include environmental targets for several impact categories, and improve their reporting and standardization throughout environment, safety, health (ESH) editions. This can be a relevant interface to bring together data and methods from the scientific community and the industrial actors, while preserving confidentiality up to a certain level. Our work in Chapter 3 could serve as a basis for this common reporting framework, as we provided all the data and assumptions. Moreover, we suggest that such a framework should integrate the ten features proposed in Chapter 3, as they have been identified as key features to be reported during the evaluation of environmental impacts of IC production. Additional features such as wafer throughput could also be of interest although this information is almost never disclosed despite its significant influence [95].

Data and tools

In their CSR, foundries should publish environmental impacts in a format that can be easily monitored through time, reused and compared to data from databases to reduce the gap from bottom-up and top-down models.

Formation and education

It is urgent and necessary to improve environmental awareness of the (future) engineers in electronics and ICT. A minimal knowledge regarding the environmental impacts of semiconductors and electronics should be integrated within the formation. More specifically, IoT designers should consider the environmental impacts generated by their devices over the whole life-cycle, both at the device and system levels.

O.5 Final thoughts

We believe this thesis improves the current knowledge of the environmental impacts of IoT devices and integrated circuits, as it brings several unique contributions to the state-of-the-art. More importantly, we hope that the approach followed in this thesis will raise awareness on the usefulness of systematic LCA for the IoT, while making clear that it is not sufficient to guarantee absolute environmental sustainability.

More generally, we should learn from the environmental lessons of the Great Acceleration which highlights the undeniable presence of rebound effects and strongly questions the expected benefits of ever-increasing technology improvements if they are used to serve unrestrained economic growth rather than the decrease of the human pressure on the environment. In particular, it is clear that LCA is a very useful tool to improve the eco-efficiency of ICT products, but its limitations must be understood. The quantification of environmental impacts should remain a mean towards the higher objective of keeping humanity within planetary limits, and not becoming a goal in itself.

Bibliography

[1] Statista, "Internet of Things (IoT) active device connections installed base worldwide from 2015 to 2025," 2021, [Online]. Available: https://www.statista.com/statistics/1101442/iot-number-of-connected-devices-worldwide/#:~:text=The%20total%20installed%20base%20of,such%20as%20computers%20and%20cellphones.

[2] Gartner, "Press release: Gartner Identifies Top 10 Strategic IoT Technologies and Trends," 2018, [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2018-11-07-gartner-identifies-top-10-strategic-iot-technologies-and-trends.

[3] CISCO, "CISCO Annual Internet Report (2018–2023) White Paper," 2020, [Online]. Available: https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html.

[4] P. Sparks, "The route to a trillion devices," *White Paper, ARM*, 2017, https://community.arm.com/cfs-file/__key/telligent-evolution-components-attachments/01-1996-00-00-00-01-30-09/Arm-_2D00_-The-route-to-a-trillion-devices-_2D00_-June-2017.pdf.

[5] L. Strous and V. G. Cerf, *Internet of Things. Information Processing in an Increasingly Connected World*. Springer Nature, 2019, https://www.springer.com/gp/book/9783030156503.

[6] International Telecommunication Union (ITU), "Internet Waste: Geneva: International Telecommunication Union and the WEEE Forum (Licence: CC BY-NC-SA 3.0 IGO)," 2020, [Online]. Available: https://www.itu.int/myitu/-/media/Publications/2020-Publications/Internet-Waste-2020.pdf.

[7] E. Ingemarsdotter, E. Jamsin, G. Kortuem, and R. Balkenende, "Circular strategies enabled by the Internet of Things - A framework and analysis of current practice," *Sustainability*, vol. 11, no. 20, p. 5689, 2019, https://doi.org/10.3390/su11205689.

[8] G. van Capelleveen, J. Pohl, A. Fritsch, and D. Schien, "The Footprint of Things: A hybrid approach towards the collection, storage and distribution of life cycle inventory data," in *ICT4S2018. 5th International Conference on Information and Communication Technology for Sustainability*, ser. EPiC Series in Computing, B. Penzenstadler, S. Easterbrook, C. Venters, and S. I. Ahmed, Eds., vol. 52. EasyChair, 2018, pp. 350–364, https://doi.org/10.29007/8pnj.

[9] S. Mishra and S. P. Singh, "Carbon management framework for sustainable manufacturing using life cycle assessment, IoT and carbon sequestration," *Benchmarking: An International Journal*, 2019, https://doi.org/10.1108/BIJ-01-2019-0044.

[10] G. Mois, S. Folea, and T. Sanislav, "Analysis of three IoT-based wireless sensors for environmental monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 8, pp. 2056–2064, 2017, https://doi.org/10.1109/TIM.2017.2677619.

[11] F. Tao, Y. Zuo, L. Da Xu, L. Lv, and L. Zhang, "Internet of things and BOM-based life cycle assessment of energy-saving and emission-reduction of products," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 2, pp. 1252–1261, 2014, https://doi.org/10.1109/TII.2014.2306771.

[12] E. Ingemarsdotter, D. Diener, S. Andersson, C. Jonasson, A.-C. Mellquist, T. Nyström, E. Jamsin, and R. Balkenende, "Quantifying the net environmental impact of using iot to support circular strategies—the case of heavy-duty truck tires in Sweden," *Circular Economy and Sustainability*, vol. 1, no. 2, pp. 613–650, 2021, https://doi.org/10.1007/s43615-021-00009-0.

[13] A. Plepys, "The grey side of ICT," *Environmental impact assessment review*, vol. 22, no. 5, pp. 509–523, 2002, https://doi.org/10.1016/S0195-9255(02)00025-2.

[14] L. M. Hilty and B. Aebischer, "ICT for sustainability: An emerging research field," *ICT innovations for Sustainability*, pp. 3–36, 2015, https://doi.org/10.1007/978-3-319-09228-7_1.

[15] F. Berkhout and J. Hertin, "Impacts of information and communication technologies on environmental sustainability: Speculations and evidence," *Report to the OECD, Brighton*, vol. 21, 2001, https://www.oecd.org/sti/inno/1897156.pdf. [Online]. Available: https://www.oecd.org/science/inno/1897156.pdf

[16] International Organization for Standardization, "ISO14040:2006 Environmental management – Life cycle assessment – Principles and framework," 2006, [Online]. Available: https://www.iso.org/standard/37456.html.

[17] European Commission - Joint Research Centre (JRC) - Institute for Environment and Sustainability, "International Reference Life Cycle Data System (ILCD) Handbook–General guide for Life Cycle Assessment-Detailed

guidance," *March*, 2010, https://eplca.jrc.ec.europa.eu/uploads/ILCD-Handbook-General-guide-for-LCA-DETAILED-GUIDANCE-12March2010-ISBN-fin-v1.0-EN.pdf.

[18] P. Teehan, "Integrative approaches to environmental life cycle assessment of consumer electronics and connected media," Ph.D. dissertation, University of British Columbia, 2014, https://doi.org/10.14288/1.0167496.

[19] L-P. P.-V.P. Clément, Q. E. S. Jacquemotte, and L.M. Hilty, "Sources of variation in life cycle assessments of smartphones and tablet computers," *Environ. Impact Assessment Rev.*, vol. 84, p. 106416, Sep. 2020, https://doi.org/10.1016/j.eiar.2020.106416.

[20] M. Ercan, J. Malmodin, P. Bergmark, E. Kimfalk, and E. Nilsson, "Life cycle assessment of a smartphone," in *ICT for Sustainability 2016*. Atlantis Press, 2016, pp. 124–133, https://dx.doi.org/10.2991/ict4s-16.2016.15.

[21] J. Aslan, K. Mayers, J. G. Koomey, and C. France, "Electricity intensity of internet data transmission: Untangling the estimates," *Journal of industrial ecology*, vol. 22, no. 4, pp. 785–798, 2018, https://doi.org/10.1111/jiec.12630.

[22] J. Malmodin, D. Lundén, Å. Moberg, G. Andersson, and M. Nilsson, "Life cycle assessment of ICT: Carbon footprint and operational electricity use from the operator, national, and subscriber perspective in Sweden," *Journal of Industrial Ecology*, vol. 18, no. 6, pp. 829–845, 2014, https://doi.org/10.1111/jiec.12145.

[23] E. R. Masanet, R. E. Brown, A. Shehabi, J. G. Koomey, and B. Nordman, "Estimating the energy use and efficiency potential of US data centers," *Proceedings of the IEEE*, vol. 99, no. 8, pp. 1440–1453, 2011, https://doi.org/10.1109/JPROC.2011.2155610.

[24] E. Masanet, A. Shehabi, N. Lei, S. Smith, and J. Koomey, "Recalibrating global data center energy-use estimates," *Science*, vol. 367, no. 6481, pp. 984–986, 2020, https://doi.org/10.1126/science.aba3758.

[25] G. Kamiya, "The carbon footprint of streaming video: fact-checking the headlines," 2020, https://policycommons.net/artifacts/1343430/the-carbon-footprint-of-streaming-video/1955576/.

[26] C. Freitag, M. Berners-Lee, K. Widdicks, B. Knowles, G. S. Blair, and A. Friday, "The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations," *Patterns*, vol. 2, no. 9, p. 100340, 2021, https://doi.org/10.1016/j.patter.2021.100340.

[27] J. C. Bieser, R. Hintemann, L. M. Hilty, and S. Beucker, "A review of assessments of the greenhouse gas footprint and abatement potential of information and communication technology," *Environmental Impact Assessment Review*, vol. 99, p. 107033, 2023, https://doi.org/10.1016/j.eiar.2022.107033.

[28] M. Stead, P. Coulton, J. Lindley, and C. Coulton, *The Little Book of Sustainability for the Internet of Things*. Imagination Lancaster, 2019, https://eprints.lancs.ac.uk/id/eprint/131084.

[29] S. Nižetić, P. Šolić, D. L.-d.-I. González-de, L. Patrono *et al.*, "Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future," *Journal of Cleaner Production*, vol. 274, p. 122877, 2020, https://doi.org/10.1016/j.jclepro.2020.122877.

[30] L. Belkhir and A. Elmeligi, "Assessing ICT global emissions footprint: Trends to 2040 & recommendations," *Journal of Cleaner Production*, vol. 177, pp. 448–463, 2018, https://doi.org/10.1016/j.jclepro.2017.12.239.

[31] International Energy Agency (IEA), "4E EDNA: Total Energy Model for Connected Devices," 2019, [Online]. Available: https://www.iea-4e.org/wp-content/uploads/publications/2019/06/A2b_-_EDNA_TEM_Report_V1.0.pdf.

[32] C. Gray, "Energy consumption of internet of things applications and services," Ph.D. dissertation, The University of Melbourne, 2018, http://hdl.handle.net/11343/224197.

[33] A. Bjørn, M. Diamond, M. Owsianiak, B. Verzat, and M. Z. Hauschild, "Strengthening the link between life cycle assessment and indicators for absolute sustainability to support development within planetary boundaries," 2015, https://doi.org/10.1021/acs.est.5b02106.

[34] W. Steffen, K. Richardson, J. Rockström, S. E. Cornell, I. Fetzer, E. M. Bennett, R. Biggs, S. R. Carpenter, W. De Vries, C. A. De Wit *et al.*, "Planetary boundaries: Guiding human development on a changing planet," *Science*, vol. 347, no. 6223, p. 1259855, 2015, https://doi.org/10.1126/science.1259855.

[35] Intergovernmental Panel on Climate Change (IPCC), "Climate change 2023: Mitigation of climate change," 2022, [Online]. Available: https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_FullReport.pdf.

[36] W. Steffen and J. Morgan, "From the Paris agreement to the anthropocene and planetary boundaries framework: An interview with Will Steffen," *Globalizations*, vol. 18, no. 7, pp. 1298–1310, 2021, https://doi.org/10.1080/14747731.2021.1940070.

[37] J. Rockström, W. Steffen, K. Noone, Å. Persson, F. S. Chapin, E. F. Lambin, T. M. Lenton, M. Scheffer, C. Folke, H. J. Schellnhuber *et al.*, "A safe operating space for humanity," *nature*, vol. 461, no. 7263, pp. 472–475, 2009, https://doi.org/10.1038/461472a.

[38] L. Wang-Erlandsson, A. Tobian, R. J. van der Ent, I. Fetzer, S. te Wierik, M. Porkka, A. Staal, F. Jaramillo, H. Dahlmann, C. Singh *et al.*, "A plane-

tary boundary for green water," *Nature Reviews Earth & Environment*, vol. 3, no. 6, pp. 380–392, 2022, https://doi.org/10.1038/s43017-022-00287-8.

[39] L. Persson, B. M. Carney Almroth, C. D. Collins, S. Cornell, C. A. de Wit, M. L. Diamond, P. Fantke, M. Hasselloöv, M. MacLeod, M. W. Ryberg *et al.*, "Outside the safe operating space of the planetary boundary for novel entities," *Environmental Science & Technology*, vol. 56, no. 3, pp. 1510–1521, 2022, https://doi.org/10.1021/acs.est.1c04158.

[40] W. Steffen, W. Broadgate, L. Deutsch, O. Gaffney, and C. Ludwig, "The trajectory of the Anthropocene: The Great Acceleration," *The Anthropocene Review*, vol. 2, no. 1, pp. 81–98, 2015, https://doi.org/10.1177/2053019614564785.

[41] W. Steffen, P. J. Crutzen, J. R. McNeill *et al.*, "The Anthropocene: Are Humans Now Overwhelming the Great Forces of Nature?" *Ambio-Journal of Human Environment Research and Management*, vol. 36, no. 8, pp. 614–621, 2007, https://www.jstor.org/stable/25547826.

[42] Intergovernmental Panel on Climate Change (IPCC), "Climate change 2022: Impacts, adaptation and vulnerability," 2022, [Online]. Available: https://www.ipcc.ch/report/ar6/wg2/.

[43] Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), "Summary for policymakers of the global assessment report on biodiversity and ecosystem services," 2019, https://doi.org/10.5281/zenodo.3553579.

[44] J. Manyika, M. Chui, P. Bisson, J. Woetzel, R. Dobbs, J. Bughin, and D. A. Dobbs, "The Internet of Things: Mapping the value beyond the hype," 2015.

[45] E. Quisbert-Trujillo, "Design methodology for sustainable IoT systems," Ph.D. dissertation, Université Grenoble Alpes [2020-....], 2022. [Online]. Available: https://hal-cea.archives-ouvertes.fr/tel-03923927/

[46] D. Bol, J. De Vos, F. Botman, G. de Streel, S. Bernard, D. Flandre, and J.-D. Legat, "Green SoCs for a sustainable Internet-of-Things," in *2013 IEEE Faible Tension Faible Consommation*. IEEE, 2013, pp. 1–4, https://doi.org/10.1109/FTFC.2013.6577767.

[47] D. Bol, G. de Streel, and D. Flandre, "Can we connect trillions of IoT sensors in a sustainable way? A technology/circuit perspective," in *2015 IEEE SOI-3D-Subthreshold Microelectronics Technology Unified Conference (S3S)*. IEEE, 2015, pp. 1–3, https://doi.org/10.1109/S3S.2015.7333500.

[48] M. Z. Hauschild, "Better–but is it good enough? On the need to consider both eco-efficiency and eco-effectiveness to gauge industrial sustainability," *Procedia CIRP*, vol. 29, pp. 1–7, 2015, https://doi.org/10.1016/j.procir.2015.02.126.

[49] A. Bjørn and M. Z. Hauschild, "Introducing carrying capacity-based normalisation in LCA: framework and development of references at midpoint level," *The International Journal of Life Cycle Assessment*, vol. 20, pp. 1005–1018, 2015, https://doi.org/10.1007/s11367-015-0899-2.

[50] A. Bjørn, "Better, but good enough? Indicators for absolute environmental sustainability in a life cycle perspective," Ph.D. dissertation, DTU Management Engineering, 2015. [Online]. Available: https://backend.orbit.dtu.dk/ws/portalfiles/portal/118946760/Better_but_good_enough.pdf

[51] M. Z. Hauschild, R. K. Rosenbaum, and S. I. Olsen, *Life cycle assessment*. Springer, 2018, https://doi.org/10.1007/978-3-319-56475-3.

[52] P. Crutzen, "Geology of mankind," *Nature*, vol. 415, no. 23, 2002, https://doi.org/10.1038/415023a.

[53] Intergovernmental Panel on Climate Change (IPCC), "Climate Change 2021–The Physical Science Basis: Summary for Policymakers," 2021, [Online]. Available: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM_final.pdf#page=33.

[54] K. Raworth, *A safe and just space for humanity: can we live within the doughnut?* Oxfam, 2012. [Online]. Available: https://www-cdn.oxfam.org/s3fs-public/file_attachments/dp-a-safe-and-just-space-for-humanity-130212-en_5.pdf

[55] ——, "A Doughnut for the Anthropocene: humanity's compass in the 21st century," *The lancet planetary health*, vol. 1, no. 2, pp. e48–e49, 2017, https://doi.org/10.1016/S2542-5196(17)30028-1.

[56] UN Department of Economic and Social Affairs, "Sustainable development goals," [Online]. Available: https://sdgs.un.org/goals.

[57] J. Rockström, J. Gupta, D. Qin, S. J. Lade, J. F. Abrams, L. S. Andersen, D. I. Armstrong McKay, X. Bai, G. Bala, S. E. Bunn *et al.*, "Safe and just Earth system boundaries," *Nature*, pp. 1–10, 2023. [Online]. Available: https://doi.org/10.1038/s41586-023-06083-8

[58] "Climate Change 2014: Synthesis report," IPCC, Geneva, Switzerland, [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/05/SYR_AR5_FINAL_full_wcover.pdf.

[59] R. K. Pachauri, M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, L. Clarke, Q. Dahe, P. Dasgupta *et al.*, *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. IPCC, 2014, https://epic.awi.de/id/eprint/37530/1/IPCC_AR5_SYR_Final.pdf.

[60] United Nations, "Paris Agreement," 2015, [Online]. Available: https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

[61] D. Pargman, A. Biørn-Hansen, E. Eriksson, J. Laaksolahti, and M. Robèrt, "From Moore's Law to the Carbon Law," in *Proceedings of the 7th International Conference on ICT for Sustainability*, 2020, pp. 285–293, https://doi.org/10.1145/3401335.3401825.

[62] J. Rockström, O. Gaffney, J. Rogelj, M. Meinshausen, N. Nakicenovic, and H. J. Schellnhuber, "A roadmap for rapid decarbonization," *Science*, vol. 355, no. 6331, pp. 1269–1271, 2017, https://doi.org/10.1126/science.aah3443.

[63] United Nations Environment Program, "Emissions Gap Report 2019. Executive summary. United Nations Environment Programme, Nairobi." 2019, [Online]. Available: https://wedocs.unep.org/bitstream/handle/20.500.11822/30798/EGR19ESEN.pdf?sequence=13.

[64] "Science Based Targets – Ambitious corporate climate action," 2023, [Online]. Available: https://sciencebasedtargets.org/.

[65] United Nations, Department of Economic and Social Affairs Statistics Division, "International Standard Industrial Classification of All Economic Activities – Revision 4," 2008, [Online]. Available: https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf.

[66] E. Lees Perasso, C. Vateau, F. Domon *et al.*, "Evaluation de l'impact environmental du numérique en France et analyse prospective," 2022, [Online]. Available: https://www.arcep.fr/uploads/tx_gspublication/etude-prospective-2030-2050_mars2023.pdf.

[67] S. Li, L. D. Xu, and S. Zhao, "The internet of things: a survey," *Information systems frontiers*, vol. 17, pp. 243–259, 2015, https://doi.org/10.1007/s10796-014-9492-7.

[68] International Telecommunication Union (ITU), "Recommendation ITU-T Y.2060: Overview of the Internet of things," 2018, [Online]. Available: https://www.itu.int/rec/T-REC-Y.2060-201206-I/en.

[69] IoT Analytics, "Our Coverage," 2023, [Online]. Available: https://iot-analytics.com/our-coverage/.

[70] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer networks*, vol. 54, no. 15, pp. 2787–2805, 2010, https://doi.org/10.1016/j.comnet.2010.05.010.

[71] J. Malmodin and D. Lundén, "The energy and carbon footprint of the global ICT and E&M sectors 2010–2015," *Sustainability*, vol. 10, no. 9, p. 3027, 2018, https://doi.org/10.3390/su10093027.

[72] International Telecommunication Union (ITU), "Recommendation ITU-T L.1410: Methodology for environmental life cycle assessments of information and communication technology goods, networks and services," 2014, [Online]. Available: https://www.itu.int/rec/T-REC-L.1410.

[73] L. M. Hilty and B. Aebischer, *ICT innovations for sustainability*. Springer, 2015, vol. 310, https://doi.org/10.1007/978-3-319-09228-7.

[74] L. Grimal, N. Burger, I. di Loreto, and N. Troussier, "Design of an interdisciplinary evaluation method for multi-scaled sustainability of computer-based projects. A work based on the Sustainable Computing Evaluation Framework (SCEF)," in *LIMITS Workshop on Computing within Limits*, 2021, https://doi.org/10.21428/bf6fb269.2ee80cf1.

[75] F. Berkhout and J. Hertin, "De-materialising and re-materialising: digital technologies and the environment," *Futures*, vol. 36, no. 8, pp. 903–920, 2004, https://doi.org/10.1016/j.futures.2004.01.003.

[76] C. Gossart, "Rebound effects and ICT: a review of the literature," *ICT innovations for sustainability*, pp. 435–448, 2015, https://doi.org/10.1007/978-3-319-09228-7_26.

[77] E. Williams, "Environmental effects of information and communications technologies," *Nature*, vol. 479, no. 7373, pp. 354–358, 2011, https://doi.org/10.1038/nature10682.

[78] H. J. Walnum, C. Aall, and S. Løkke, "Can rebound effects explain why sustainable mobility has not been achieved?" *Sustainability*, vol. 6, no. 12, pp. 9510–9537, 2014, https://doi.org/10.3390/su6129510.

[79] S. Sorrell *et al.*, "The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency," 2007, [Online]. Available: https://ukerc.ac.uk/publications/the-rebound-effect-an-assessment-of-the-evidence-for-economy-wide-energy-savings-from-improved-energy-efficiency/.

[80] B. Alcott, M. Giampietro, K. Mayumi, and J. Polimeni, *The Jevons paradox and the myth of resource efficiency improvements*. Routledge, 2012, https://doi.org/10.4324/9781849773102.

[81] L. M. Hilty, B. Aebischer, and A. E. Rizzoli, "Modeling and evaluating the sustainability of smart solutions," 2014, https://doi.org/10.1016/j.envsoft.2014.04.001.

[82] V. C. Coroamă, P. Bergmark, M. Höjer, and J. Malmodin, "A Methodology for Assessing the Environmental Effects Induced by ICT Services: Part I: Single Services," in *Proceedings of the 7th International Conference on ICT for Sustainability*, 2020, pp. 36–45, https://doi.org/10.1145/3401335.3401716.

[83] G. Wallenborn, "Rebounds are structural effects of infrastructures and markets," *Frontiers in energy research*, vol. 6, p. 99, 2018, https://doi.org/10.3389/fenrg.2018.00099.

[84] M. Binswanger, "Technological progress and sustainable development: what about the rebound effect?" *Ecological economics*, vol. 36, no. 1, pp. 119–132, 2001, https://doi.org/10.1016/S0921-8009(00)00214-7.

[85] F. Schneider, "Sur l'importance de la décroissance des capacités de production et de consommation dans le Nord Global pour éviter l'Effet Rebond," *La décroissance économique (Pour la soutenabilité écologique et l'équité sociale)*, pp. 197–214, 2009, https://www.degrowth.org/wp-content/uploads/2011/08/D%C3%A9croissancecapacit%C3%A9scroquant.pdf.

[86] S. Lange, F. Kern, J. Peuckert, and T. Santarius, "The Jevons paradox unravelled: A multi-level typology of rebound effects and mechanisms," *Energy Research & Social Science*, vol. 74, p. 101982, 2021, https://doi.org/10.1016/j.erss.2021.101982.

[87] F. Bordage, L. de Montenay, S. Benqassem, J. DelmasOrgelet, F. Domon, D. Prunel, C. Vateau, E. Lees Perasso, and GreenIT.fr, "Behind the figures: understanding the environmental impacts of ICT and taking action," 2021, [Online]. Available: https://www.apl-datacenter.com/wp-content/uploads/2021/12/Case-studies-Environnemental-impacts-of-ICT-and-Digital-technologies-7-dec-2021.pdf.

[88] P. H. Berkhout, J. C. Muskens, and J. W. Velthuijsen, "Defining the rebound effect," *Energy policy*, vol. 28, no. 6-7, pp. 425–432, 2000, https://doi.org/10.1016/S0301-4215(00)00022-7.

[89] M. B. Rivera, C. Håkansson, Å. Svenfelt, and G. Finnveden, "Including second order effects in environmental assessments of ICT," *Environmental Modelling & Software*, vol. 56, pp. 105–115, 2014, https://doi.org/10.1016/j.envsoft.2014.02.005.

[90] Global e-Sustainability Initiative (GeSI), "SMARTer2030, ICT solutions for 21st century challenges," *Executive Summary: ICT Solutions for 21st Century Challenges*, vol. 8, 2015. [Online]. Available: https://unfccc.int/sites/default/files/smarter2030_executive_summary.pdf

[91] A. Rasoldier, J. Combaz, A. Girault, K. Marquet, and S. Quinton, "How realistic are claims about the benefits of using digital technologies for GHG emissions mitigation?" *Proceedings of the LIMITS conference*, 2022. [Online]. Available: https://computingwithinlimits.org/2022/papers/limits22-final-Rasoldier.pdf

[92] U. Gupta, M. Elgamal, G. Hills, G.-Y. Wei, H.-H. S. Lee, D. Brooks, and C.-J. Wu, "ACT: Designing sustainable computer systems with an architectural carbon modeling tool," in *Proceedings of the 49th Annual International Symposium on Computer Architecture*, 2022, pp. 784–799, https://doi.org/10.1145/3470496.3527408.

[93] A. Lelah, F. Mathieux, and D. Brissaud, "Contributions to eco-design of machine-to-machine product service systems: the example of waste glass collection," *Journal of Cleaner Production*, vol. 19, no. 9-10, pp. 1033–1044, 2011, https://doi.org/10.1016/j.jclepro.2011.02.003.

[94] S. B. Boyd, *Life-cycle assessment of semiconductors*. Springer Science & Business Media, 2011, https://doi.org/10.1007/978-1-4419-9988-7.

[95] M. G. Bardon, P. Wuytens, L.-Å. Ragnarsson, G. Mirabelli, D. Jang, G. Willems, A. Mallik, A. Spessot, J. Ryckaert, and B. Parvais, "DTCO including sustainability: Power-performance-area-cost-environmental score (PPACE) analysis for logic technologies," in *2020 IEEE International Electron Devices Meeting (IEDM)*. IEEE, 2020, pp. 41–4, https://doi.org/10.1109/IEDM13553.2020.9372004.

[96] S. Cucurachi, C. F. Blanco, B. Steubing, and R. Heijungs, "Implementation of uncertainty analysis and moment-independent global sensitivity analysis for full-scale life cycle assessment models," *Journal of Industrial Ecology*, vol. 26, no. 2, pp. 374–391, 2022, https://doi.org/10.1111/jiec.13194.

[97] A. Villard, A. Lelah, and D. Brissaud, "Drawing a chip environmental profile: environmental indicators for the semiconductor industry," *J. of Cleaner Prod.*, vol. 86, pp. 98–109, Jan. 2015, https://doi.org/10.1016/j.jclepro.2014.08.061.

[98] C. F. Murphy, G. A. Kenig, D. T. Allen, J.-P. Laurent, and D. E. Dyer, "Development of parametric material, energy, and emission inventories for wafer fabrication in the semiconductor industry," *Environmental Science & Technology*, vol. 37, no. 23, pp. 5373–5382, 2003, https://doi.org/10.1021/es034434g.

[99] C. F. Murphy, J.-P. Laurent, and D. T. Allen, "Life cycle inventory development for wafer fabrication in semiconductor manufacturing," in *IEEE Int. Symp. on Electronics and the Environ., 2003.*, May 2003, pp. 276–281, https://doi.org/10.1109/ISEE.2003.1208089.

[100] A. K. Jones, Y. Chen, W. O. Collinge, H. Xu, L. A. Schaefer, A. E. Landis, and M. M. Bilec, "Considering fabrication in sustainable computing," in *2013 IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*. IEEE, 2013, pp. 206–210, https://doi.org/10.1109/ICCAD.2013.6691120.

[101] P. Teehan and M. Kandlikar, "Comparing embodied greenhouse gas emissions of modern computing and electronics products," *Environmental Science & Technology*, vol. 47, no. 9, pp. 3997–4003, 2013, https://doi.org/10.1021/es303012r.

[102] T. Higgs, M. Cullen, M. Yao, and S. Stewart, "Review of LCA methods for ICT products and the impact of high purity and high cost materials," in *Proc. of the IEEE Int. Symp. on Sustain. Syst. and Technol.*, May 2010, pp. 1–6, https://doi.org/10.1109/ISSST.2010.5507691.

[103] H. S. Matthews and M. J. Small, "Extending the boundaries of life-cycle assessment through environmental economic input-output models," *J. of Ind. Ecology*, vol. 4, no. 3, pp. 7–10, 2000, https://doi.org/10.1162/108819800300106357.

[104] N. Krishnan, S. Boyd, A. Somani, S. Raoux, D. Clark, and D. Dornfeld, "A hybrid life cycle inventory of nano-scale semiconductor manufacturing," *Environmental Science & Technology*, vol. 42, no. 8, pp. 3069–3075, 2008, https://doi.org/10.1021/es071174k.

[105] M. Buyle, A. Audenaert, P. Billen, K. Boonen, and S. Van Passel, "The future of ex-ante LCA? Lessons learned and practical recommendations," *Sustainability*, vol. 11, no. 19, p. 5456, 2019, https://doi.org/10.3390/su11195456.

[106] C. De Camillis, M. Brandão, A. Zamagni, and D. Pennington, "Sustainability assessment of future-oriented scenarios: a review of data modelling approaches in Life Cycle Assessment," *Towards Recommendations for Policy Making and Business Strategies*, pp. 1–90, 2013, http://dx.doi.org/10.2788/95227.

[107] A. Zamagni, J. Guinée, R. Heijungs, P. Masoni, and A. Raggi, "Lights and shadows in consequential LCA," *The International Journal of Life Cycle Assessment*, vol. 17, pp. 904–918, 2012, https://doi.org/10.1007/s11367-012-0423-x.

[108] T. Ekvall, A. Azapagic, G. Finnveden, T. Rydberg, B. P. Weidema, and A. Zamagni, "Attributional and consequential LCA in the ILCD handbook," *The International Journal of Life Cycle Assessment*, vol. 21, pp. 293–296, 2016, https://doi.org/10.1007/s11367-015-1026-0.

[109] European Telecommunications Standards Institute, "ETSI Technical Specification 103 199 V1.1.1: Environmental Engineering (EE)–Life Cycle Assessment (LCA) of ICT equipment, networks and services–General methodology and common requirements," 2011, [Online]. Available: https://www.etsi.org/deliver/etsi_ts/103100_103199/103199/01.01.01_60/ts_103199v010101p.pdf.

[110] Y. Arushanyan, E. Ekener-Petersen, and G. Finnveden, "Lessons learned–Review of LCAs for ICT products and services," *Comput. in Ind.*, vol. 65, no. 2, pp. 211–234, Feb. 2014, https://doi.org/10.1016/j.compind.2013.10.003.

[111] A. Plepys, "The environmental impacts of electronics: going beyond the walls of semiconductor fabs," in *IEEE Int. Symp. on Electronics and the Environ.*, May 2004, pp. 159–165, https://doi.org/10.1109/ISEE.2004.1299707.

[112] Sphera, "GaBi extension database XI : Electronics," 2022, [Online]. Available: https://sphera.com/product-sustainability-gabi-data-search/.

[113] G. Soós, D. Kozma, F. N. Janky, and P. Varga, "IoT device lifecycle - A generic model and a use case for cellular mobile networks," in *2018 IEEE 6th International Conference on Future Internet of Things and Cloud (FiCloud)*. IEEE, 2018, pp. 176–183, https://doi.org/10.1109/FiCloud.2018.00033.

[114] L. F. Rahman, T. Ozcelebi, and J. Lukkien, "Understanding IoT systems: a life cycle approach," *Procedia computer science*, vol. 130, pp. 1057–1062, 2018, https://doi.org/10.1016/j.procs.2018.04.148.

[115] S. Nižetić, N. Djilali, A. Papadopoulos, and J. J. Rodrigues, "Smart technologies for promotion of energy efficiency, utilization of sustainable resources and waste management," *Journal of Cleaner Production*, vol. 231, pp. 565–591, 2019, https://doi.org/10.1016/j.jclepro.2019.04.397.

[116] S. Van Dam, C. Bakker, and J. Buiter, "Do home energy management systems make sense? Assessing their overall lifecycle impact," *Energy Policy*, vol. 63, pp. 398–407, 2013, https://doi.org/10.1016/j.enpol.2013.09.041.

[117] S. Van Dam, *Smart energy management for households*. TU Delft, 2013, https://doi.org/10.7480/abe.2013.5.

[118] O. Bates and M. Hazas, "Exploring the hidden impacts of HomeSys: energy and emissions of home sensing and automation," in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, 2013, pp. 809–814, https://doi.org/10.1145/2494091.2497322.

[119] J.-N. Louis, A. Calo, K. Leiviskä, and E. Pongrácz, "Environmental impacts and benefits of smart home automation: Life cycle assessment of home energy management system," *IFAC-PapersOnLine*, vol. 48, no. 1, pp. 880–885, 2015, https://doi.org/10.1016/j.ifacol.2015.05.158.

[120] N. M. Van der Velden, K. Kuusk, and A. R. Köhler, "Life cycle assessment and eco-design of smart textiles: The importance of material selection demonstrated through e-textile product redesign," *Materials & Design*, vol. 84, pp. 313–324, 2015, https://doi.org/10.1016/j.matdes.2015.06.129.

[121] O. Gurova, T. R. Merritt, E. Papachristos, and J. Vaajakari, "Sustainable Solutions for Wearable Technologies: Mapping the Product Development Life Cycle," *Sustainability*, vol. 12, no. 20, p. 8444, 2020, https://doi.org/10.3390/su12208444.

[122] K. Schischke, N. F. Nissen, and M. Schneider-Ramelow, "Flexible, stretchable, conformal electronics, and smart textiles: environmental life cycle considerations for emerging applications," *MRS Communications*, vol. 10, no. 1, p. 69–82, 2020, https://doi.org/10.1557/mrc.2019.157.

[123] S. Kokare, "Comparative Life Cycle Assessment of Cardiac Monitoring Devices: A Case Study," 2020, [Online]. Available: https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1503537.

[124] A. R. Köhler, C. Lauterbach, A. Steinhage, J. C. Buiter, and A. Techmer, "Life cycle assessment and eco-design of a textile-based large-area sensor system," in *2012 Electronics Goes Green 2012+*. IEEE, 2012, pp. 1–8.

[125] G. Le Brun and J.-P. Raskin, "Material and manufacturing process selection for electronics eco-design: Case study on paper-based water quality sensors," *Procedia CIRP*, vol. 90, pp. 344–349, 2020, https://doi.org/10.1016/j.procir.2020.02.041.

[126] D. Bol, S. Boyd, and D. Dornfeld, "Application-aware LCA of semiconductors: Life-cycle energy of microprocessors from high-performance 32nm CPU to ultra-low-power 130nm MCU," in *Proceedings of the 2011 IEEE International Symposium on Sustainable Systems and Technology*. IEEE, 2011, pp. 1–6, https://doi.org/10.1109/ISSST.2011.5936883.

[127] J. Bonvoisin, A. Lelah, F. Mathieux, and D. Brissaud, "An environmental assessment method for wireless sensor networks," *Journal of Cleaner Production*, vol. 33, pp. 145–154, 2012, https://doi.org/10.1016/j.jclepro.2012.04.016.

[128] E. Quisbert-Trujillo, T. Ernst, K. E. Samuel, E. Cor, and E. Monnier, "Lifecycle modeling for the eco design of the Internet of Things," *Procedia CIRP*, vol. 90, pp. 97–101, 2020, https://doi.org/10.1016/j.procir.2020.02.120.

[129] J. Bonvoisin, A. Lelah, F. Mathieux, and D. Brissaud, "An integrated method for environmental assessment and ecodesign of ICT-based optimization services," *Journal of Cleaner Production*, vol. 68, pp. 144–154, 2014, https://doi.org/10.1016/j.jclepro.2014.01.003.

[130] O. Manz, S. Meyer, and C. Baumgartner, "Life cycle assessment of an Internet of Things product: Environmental impact of an intelligent smoke detector," in *Proceedings of the 11th International Conference on the Internet of Things*, 2021, pp. 72–79, https://doi.org/10.1145/3494322.3494332.

[131] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future generation computer systems*, vol. 29, no. 7, pp. 1645–1660, 2013, https://doi.org/10.1016/j.future.2013.01.010.

[132] F. Samie, L. Bauer, and J. Henkel, "IoT technologies for embedded computing: A survey," in *2016 International Conference on Hardware/Software Codesign and System Synthesis (CODES+ ISSS)*. IEEE, 2016, pp. 1–10, http://dx.doi.org/10.1145/2968456.2974004.

[133] S. Das and E. Mao, "The global energy footprint of information and communication technology electronics in connected Internet-of-Things devices," *Sustainable Energy, Grids and Networks*, vol. 24, p. 100408, 2020, https://doi.org/10.1016/j.segan.2020.100408.

[134] L. A.-W. Ellingsen, G. Majeau-Bettez, B. Singh, A. K. Srivastava, L. O. Valøen, and A. H. Strømman, "Life cycle assessment of a lithium-ion battery vehicle pack," *Journal of Industrial Ecology*, vol. 18, no. 1, pp. 113–124, 2014, https://doi.org/10.1111/jiec.12072.

[135] AUO, "Corporate Social Responsibility Report (Chapter 4 Environmental Sustainability)," 2019, [Online]. Available: https://csr.auo.com/uploads/able/files/download/5f0e4b5f07e2c.pdf.

[136] International Energy Agency (IEA), "Energy efficiency of the Internet of Things : Technology and Energy Assessment Report Prepared for IEA

4E EDNA," 2016, [Online]. Available: https://nachhaltigwirtschaften.at/resources/iea_pdf/reports/iea_4e_edna_energy_efficiency_of_the_internet_of_things_technical_report.pdf.

[137] C. W. Babbitt, H. Madaka, S. Althaf, B. Kasulaitis, and E. G. Ryen, "Disassembly-based bill of materials data for consumer electronic products," *Scientific data*, vol. 7, no. 1, pp. 1–8, 2020, https://doi.org/10.6084/m9.figshare.12513695.

[138] B. V. Kasulaitis, C. W. Babbitt, R. Kahhat, E. Williams, and E. G. Ryen, "Evolving materials, attributes, and functionality in consumer electronics: Case study of laptop computers," *Resources, conservation and recycling*, vol. 100, pp. 1–10, 2015, https://doi.org/10.1016/j.resconrec.2015.03.014.

[139] M. Proske, D. Sánchez, C. Clemm, and S.-J. Baur, "Life Cycle Assessment of the Fairphone 3," 2020, [Online]. Available: https://www.fairphone.com/wp-content/uploads/2020/07/Fairphone_3_LCA.pdf.

[140] Google, "Sustainability reports," 2020, [Online]. Available: https://sustainability.google/reports/.

[141] Apple, "Product Environmental Reports," 2020, [Online]. Available: https://www.apple.com/environment/.

[142] F.-J. Alvarado-Alcon, R. Asorey-Cacheda, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "Carbon Footprint vs Energy Optimization in IoT Network Deployments," *IEEE Access*, vol. 10, pp. 111 297–111 309, 2022, https://doi.org/10.1109/ACCESS.2022.3216377.

[143] J. Van Mulders, J. Cappelle, S. Goossens, L. De Strycker, and L. Van der Perre, "UAV-Based Servicing of IoT Nodes: Assessment of Ecological Impact," *Sensors*, vol. 23, no. 4, p. 2291, 2023, https://doi.org/10.3390/s23042291.

[144] P. Maistriaux, T. Pirson, M. Schramme, J. Louveaux, and D. Bol, "Modeling the Carbon Footprint of Battery-Powered IoT Sensor Nodes for Environmental-Monitoring Applications," in *Proceedings of the 12th International Conference on the Internet of Things*, 2022, pp. 9–16, https://doi.org/10.1145/3567445.3567448.

[145] S. Prakash, M. Stewart, C. Banbury, M. Mazumder, P. Warden, B. Plancher, and V. J. Reddi, "Is TinyML Sustainable? Assessing the Environmental Impacts of Machine Learning on Microcontrollers," *arXiv preprint arXiv:2301.11899*, 2023, https://doi.org/10.48550/arXiv.2301.11899.

[146] F. Bordage, L. de Montenay, S. Benqassem, J. DelmasOrgelet, F. Domon, D. Prunel, C. Vateau, E. Lees Perasso, and GreenIT.fr, "Digital Technologies in Europe: an environmental life cycle approach," 2021, [Online]. Available: http://extranet.greens-efa-service.eu/public/media/file/1/7388.

[147] ——, "Behind the figures: understanding the environmental impacts of ICT and taking action," 2021, [Online]. Available: https://www.greens-efa.eu/files/assets/docs/ict_environmental_impacts-behind_the_figures-5low.pdf.

[148] Bureau Veritas, "EIME: LCA and eco-design software," 2022, [Online]. Available: https://codde.fr/en/our-software/eime-presentation.

[149] Ecosystem, "WEEE LCI Database," [Online]. Available: https://weee-lci.ecosystem.eco/.

[150] Boavizta, "Evaluation d'impacts environnementaux du numérique," [Online]. Available: https://boavizta.org/.

[151] Mavana, "Conseil numérique et environnemental," [Online]. Available: https://mavana.earth/.

[152] ——, "Objets connectés (IoT) : les révélations de l'étude ADEME/ARCEP 2023," 2023, [Online]. Available: https://mavana.earth/objets-connectes-iot-les-revelations-de-letude-ademe-arcep-2023/.

[153] P. Verhulst, J. Durieux, and L. Baclin, "Analyse de l'impact environnemental de capteurs IoT," Ph.D. dissertation, Université catholique de Louvain (FUCAM, Mons), 2022, http://hdl.handle.net/2078.1/thesis:35395.

[154] M. C. Cornax, P. Lago, and C. Roncancio, "Cyber Physical Systems and Environmental Issues: a Smart Home Case Study," in *CEUR Workshop Proceedings*, vol. 3144. CEUR, 2022. [Online]. Available: https://hal.science/hal-03959660/

[155] K. Toczé, M. Madon, M. Garcia, and P. Lago, "The Dark Side of Cloud and Edge Computing: An Exploratory Study," in *8th Workshop on Computing within Limits (LIMITS 2022)*, 2022, https://doi.org/10.21428/bf6fb269.9422c084.

[156] T. Kumar, R. Srinivasan, and M. Mani, "An Emergy-based Approach to Evaluate the Effectiveness of Integrating IoT-based Sensing Systems into Smart Buildings," *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102225, 2022, https://doi.org/10.1016/j.seta.2022.102225.

[157] P. Gobinath and R. H. Crawford, "A review of life cycle sustainability assessment studies of smart building management systems," *ASA 2022*, p. 86, 2022, https://archscience.org/paper/a-review-of-life-cycle-sustainability-assessment-studies-of-smart-building-management-systems/.

[158] L. Deng and E. Williams, "Measures and trends in energy use of semiconductor manufacturing," in *IEEE Int. Symp. on Electronics and the Environ.*, May 2008, pp. 1–6, https://doi.org/10.1109/ISEE.2008.4562888.

[159] M. L. Alcaraz, A. Noshadravan, M. Zgola, R. E. Kirchain, and E. A. Olivetti, "Streamlined life cycle assessment: A case study on tablets and integrated

circuits," *J. of Cleaner Prod.*, vol. 200, pp. 819–826, Nov. 2018, https://doi.org/10.1016/j.jclepro.2018.07.273.

[160] T. Pirson and D. Bol, "Assessing the embodied carbon footprint of IoT edge devices with a bottom-up life-cycle approach," *J. of Cleaner Prod.*, vol. 322, p. 128966, Nov. 2021, https://doi.org/10.1016/j.jclepro.2021.128966.

[161] D. Kline, N. Parshook, A. Johnson, J. E. Stine, W. Stanchina, E. Brunvand, and A. K. Jones, "Sustainable IC design and fabrication," in *2017 Eighth International Green and Sustainable Computing Conference (IGSC)*. IEEE, 2017, pp. 1–8, https://doi.org/10.1109/IGCC.2017.8323572.

[162] M. S. Branham, "Semiconductors and sustainability: energy and materials use in integrated circuit manufacturing," Ph.D. dissertation, Massachusetts Institute of Technology, 2008, http://hdl.handle.net/1721.1/46056.

[163] E. D. Williams, R. U. Ayres, and M. Heller, "The 1.7 kilogram microchip: Energy and material use in the production of semiconductor devices," *Environmental Science & Technology*, vol. 36, no. 24, pp. 5504–5510, 2002, https://doi.org/10.1021/es025643o.

[164] A. S. Andrae and M. S. Vaija, "Precision of a streamlined life cycle assessment approach used in eco-rating of mobile phones," *Challenges*, vol. 8, no. 2, p. 21, 2017, https://doi.org/10.3390/challe8020021.

[165] R. Hischier, V. C. Coroama, D. Schien, and M. A. Achachlouei, "Grey energy and environmental impacts of ICT hardware," in *ICT Innovations for Sustainability*. Springer, 2015, pp. 171–189, http://dx.doi.org/10.1007/978-3-319-09228-7_10.

[166] G. E. Moore *et al.*, "Cramming more components onto integrated circuits," 1965, [Online]. Available: https://cdn3.weka-fachmedien.de/media_uploads/documents/1429521922-13-gordonmoore1965article.pdf.

[167] ——, "Moore's law at 40," 2006, [Online]. Available: https://alejandrobarros.com/wp-content/uploads/old/4363/Understanding-Moores-Law_Chapter-07.pdf.

[168] A. Plepys, "Environmental Implications of Product Servicising. - The Case of Outsourced Computing Utilities," Ph.D. dissertation, University of Lund (Sweden), 2004, https://lup.lub.lu.se/record/467251.

[169] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *International Journal of Surgery*, vol. 88, p. 105906, 2021, https://doi.org/10.1136/bmj.n71.

[170] A. Varas, R. Varadarajan, J. Goodrich, and F. Yinug, "Strengthening the global semiconductor supply chain in an uncertain era," BCG and

SIA, 2021, [Online]. Available: https://www.semiconductors.org/wp-content/uploads/2021/05/BCG-x-SIA-Strengthening-the-Global-Semiconductor-Value-Chain-April-2021_1.pdf.

[171] C. A. Mack, "Fifty years of Moore's law," *IEEE Trans. on Semicond. Manuf.*, vol. 24, no. 2, pp. 202–207, Jan. 2011, https://doi.org/10.1109/TSM.2010.2096437.

[172] M. Proske, C. Clemm, and N. Richter, "Life Cycle Assessment of the Fairphone 2," Fraunhofer IZM, 2016, [Online]. Available: https://www.fairphone.com/wp-content/uploads/2016/11/Fairphone_2_LCA_Final_20161122.pdf.

[173] Y. Wang, Y. Zhang, M. Rahimi, and M. Pedram, "A Life-Cycle Energy and Inventory Analysis of FinFET Integrated Circuits," Univ. of Southern California, Los Angeles, CA, USA, 2014, [Online]. Available: https://mpedram.com/Papers/lifecycle-inventory-analysis-finfet-issst14.pdf.

[174] R. Hischier, M. A. Achachlouei, and L. M. Hilty, "Evaluating the sustainability of electronic media: Strategies for life cycle inventory data collection and their implications for LCA results," *Environ. Model. & Softw.*, vol. 56, pp. 27–36, Jun. 2014, https://doi.org/10.1016/j.envsoft.2014.01.001.

[175] "GaBi extension database XI: Electronics," Sphera, 2022, [Online]. Available: https://gabi.sphera.com/databases/gabi-databases/electronics/.

[176] "Ecoinvent database," Ecoinvent, 2022, [Online]. Available: https://ecoinvent.org/the-ecoinvent-database/.

[177] L. Deng, C. W. Babbitt, and E. D. Williams, "Economic-balance hybrid LCA extended with uncertainty analysis: case study of a laptop computer," *J. of Cleaner Prod.*, vol. 19, no. 11, pp. 1198–1206, Jul. 2011, https://doi.org/10.1016/j.jclepro.2011.03.004.

[178] A. Nardelli, E. Deuschle, L. D. de Azevedo, J. L. N. Pessoa, and E. Ghisi, "Assessment of Light Emitting Diodes technology for general lighting: A critical review," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 368–379, 2017. [Online]. Available: https://doi.org/10.1016/j.rser.2016.11.002

[179] World Business Council for Sustainable Development (WBCSD) and World Resources Institute (WRI), "The Greenhouse Gas Protocol: A corporate accounting and reporting standard," 2004, [Online]. Available: https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf.

[180] J. C. Minx, T. Wiedmann, R. Wood, G. P. Peters, M. Lenzen, A. Owen, K. Scott, J. Barrett, K. Hubacek, G. Baiocchi *et al.*, "Input–output analysis and carbon footprinting: an overview of applications," *Economic systems research*, vol. 21, no. 3, pp. 187–216, 2009.

[181] B. T. Murphy, "Cost-size optima of monolithic integrated circuits," *Proceedings of the IEEE*, vol. 52, no. 12, pp. 1537–1545, 1964, https://doi.org/10.1109/PROC.1964.3442.

[182] N. Krishnan, E. D. Williams, and S. B. Boyd, "Case studies in energy use to realize ultra-high purities in semiconductor manufacturing," in *IEEE Int. Symp. on Electronics and the Environ.*, May 2008, pp. 1–6, https://doi.org/10.1109/ISEE.2008.4562913.

[183] P. Teehan, "Integrative approaches to environmental life cycle assessment of consumer electronics and connected media," Ph.D. dissertation, University of British Columbia, 2014. [Online]. Available: http://hdl.handle.net/2429/47025

[184] S. Prakash, R. Liu, K. Schischke, L. Stobbe, and C. Gensch, "Schaffung einer datenbasis zur ermittlung ökologischer wirkungen der produkte der informations-und kommunikationstechnik (IKT)," 2013, [Online]. Available: https://www.umweltbundesamt.de/publikationen/schaffung-einer-datenbasis-zur-ermittlung.

[185] ITRS 2.0, "Environment, Safety, and Health," 2015, [Online]. Available: https://www.semiconductors.org/wp-content/uploads/2018/06/4_2015-ITRS-2.0-ESH.pdf.

[186] M. Schmidt, H. Hottenroth, M. Schottler, G. Fetzer, and B. Schlüter, "Life cycle assessment of silicon wafer processing for microelectronic chips and solar cells," *The Int. J. of Life Cycle Assessment*, vol. 17, no. 2, pp. 126–144, 2012, https://doi.org/10.1007/s11367-011-0351-1.

[187] D. Bol, J. De Vos, C. Hocquet, F. Botman, F. Durvaux, S. Boyd, D. Flandre, and J.-D. Legat, "A 25MHz 7μW/MHz ultra-low-voltage microcontroller SoC in 65nm LP/GP CMOS for low-carbon wireless sensor nodes," in *IEEE Int. Solid-State Circuits Conf.*, Feb. 2012, pp. 490–492, https://doi.org/10.1109/ISSCC.2012.6177104.

[188] A. S. Andrae and M. S. Vaija, "To which degree does sector specific standardization make life cycle assessments comparable? The case of global warming potential of smartphones," *Challenges*, vol. 5, no. 2, pp. 409–429, Nov. 2014, https://doi.org/10.3390/challe5020409.

[189] A. S. Andrae, "Life-cycle assessment of consumer electronics: a review of methodological approaches," *IEEE Consum. Electronics Mag.*, vol. 5, no. 1, pp. 51–60, Dec. 2015, https://doi.org/10.1109/MCE.2015.2484639.

[190] L. Chen, "Dream technology 'scares people to death' TSMC's new plant consumes more electricity than the entire eastern Taiwan," 2017, [Online]. Available: https://www.cw.com.tw/article/5084341.

[191] A. Plepys, "Substituting computers for services-potential to reduce ICT's environmental footprint," in *Int. Congr. and Exhib.*

on Electronics Goes Green, 2004, pp. 217–222, [Online]. Available: https://portal.research.lu.se/en/publications/substituting-computers-for-services-potential-to-reduce-icts-envi.

[192] SEMI, "Silicon shipment statistics," 2021, [Online]. Available: https://www.semi.org/en/products-services/market-data/materials/si-shipment-statistics.

[193] Q. Wang, N. Huang, Z. Chen, X. Chen, H. Cai, and Y. Wu, "Environmental data and facts in the semiconductor manufacturing industry: An unexpected high water and energy consumption situation," *Water Cycle*, vol. 4, pp. 47–54, 2023, https://doi.org/10.1016/j.watcyc.2023.01.004.

[194] P. Nagapurkar and S. Das, "Economic and embodied energy analysis of integrated circuit manufacturing processes," *Sustainable Computing: Informatics and Systems*, vol. 35, p. 100771, 2022, https://doi.org/10.1016/j.suscom.2022.100771.

[195] T. Pirson, T. P. Delhaye, A. Pip, G. Le Brun, J.-P. Raskin, and D. Bol, "The Environmental Footprint of IC Production: Review, Analysis and Lessons from Historical Trends," *IEEE Transactions on Semiconductor Manufacturing*, 2022, https://doi.org/10.1109/TSM.2022.3228311.

[196] M. A. Huijbregts, L. J. Rombouts, S. Hellweg, R. Frischknecht, A. J. Hendriks, D. Van de Meent, A. M. Ragas, L. Reijnders, and J. Struijs, "Is cumulative fossil energy demand a useful indicator for the environmental performance of products?" 2006. [Online]. Available: https://doi.org/10.1021/es051689g

[197] M. Dubberley, A. M. Agogino, and A. Horvath, "Life-cycle assessment of an intelligent lighting system using a distributed wireless mote network," in *IEEE International Symposium on Electronics and the Environment, 2004. Conference Record. 2004*. IEEE, 2004, pp. 122–127, https://doi.org/10.1109/ISEE.2004.1299700.

[198] J. A. Manrique, J. S. Rueda-Rueda, and J. M. Portocarrero, "Contrasting internet of things and wireless sensor network from a conceptual overview," in *2016 IEEE international conference on Internet of Things (iThings) and IEEE green computing and communications (GreenCom) and IEEE cyber, physical and social computing (CPSCom) and IEEE smart data (SmartData)*. IEEE, 2016, pp. 252–257, https://doi.org/10.1109/iThings-GreenCom-CPSCom-SmartData.2016.66.

[199] Wirepass, "The best mesh for IoT," 2023, [Online]. Available: https://www.wirepas.com/products/how-it-works.

[200] V. C. Coroama and L. M. Hilty, "Assessing Internet energy intensity: A review of methods and results," *Environmental impact assessment review*, vol. 45, pp. 63–68, 2014, https://doi.org/10.1016/j.eiar.2013.12.004.

[201] H. Pihkola, M. Hongisto, O. Apilo, and M. Lasanen, "Evaluating the energy consumption of mobile data transfer—from technology development to consumer behaviour and life cycle thinking," *Sustainability*, vol. 10, no. 7, p. 2494, 2018, https://doi.org/10.3390/su10072494.

[202] L. Golard, J. Louveaux, and D. Bol, "Evaluation and projection of 4G and 5G RAN energy footprints: the case of Belgium for 2020–2025," *Annals of Telecommunications*, pp. 1–15, 2022, https://doi.org/10.1007/s12243-022-00932-9.

[203] D. Schien, P. Shabajee, M. Yearworth, and C. Preist, "Modeling and assessing variability in energy consumption during the use stage of online multimedia services," *Journal of Industrial Ecology*, vol. 17, no. 6, pp. 800–813, 2013, https://doi.org/10.1111/jiec.12065.

[204] A. S. Andrae and T. Edler, "On global electricity usage of communication technology: trends to 2030," *Challenges*, vol. 6, no. 1, pp. 117–157, 2015, https://doi.org/10.3390/challe6010117.

[205] J. Baliga, R. W. Ayre, K. Hinton, and R. S. Tucker, "Green cloud computing: Balancing energy in processing, storage, and transport," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 149–167, 2010. [Online]. Available: https://doi.org/10.1109/JPROC.2010.2060451

[206] V. C. Coroama, L. M. Hilty, E. Heiri, and F. M. Horn, "The direct energy demand of internet data flows," *Journal of Industrial Ecology*, vol. 17, no. 5, pp. 680–688, 2013, https://doi.org/10.1111/jiec.12048.

[207] D. Schien and C. Preist, "Approaches to energy intensity of the internet," *IEEE Communications Magazine*, vol. 52, no. 11, pp. 130–137, 2014, https://doi.org/10.1109/MCOM.2014.6957153.

[208] J. Malmodin, D. Lundén, M. Nilsson, and G. Andersson, "LCA of data transmission and IP core networks," in *2012 Electronics Goes Green 2012+*. IEEE, 2012, pp. 1–6.

[209] Å. Moberg, C. Borggren, C. Ambell, G. Finnveden, F. Guldbrandsson, A. Bondesson, J. Malmodin, and P. Bergmark, "Simplifying a life cycle assessment of a mobile phone," *The International Journal of Life Cycle Assessment*, vol. 19, pp. 979–993, 2014, https://doi.org/10.1007/s11367-014-0721-6.

[210] World Economic Forum, "A New Circular Vision for Electronics - Time for a Global Reboot," 2019, [Online]. Available: http://www3.weforum.org/docs/WEF_A_New_Circular_Vision_for_Electronics.pdf.

[211] V. Forti, C. Balde, R. Kuehr, and G. Bel, "The Global E-waste Monitor 2020: Quantities, flows and the circular economy potential," 2020, [Online]. Available: https://www.itu.int/en/ITU-D/Environment/Documents/Toolbox/GEM_2020_def.pdf.

[212] T. Lehmann and T. J. Hamilton, "Integrated circuits towards reducing e-waste: Future design directions," in *The 2010 International Conference on Green Circuits and Systems*. IEEE, 2010, pp. 469–472, https://doi.org/10.1109/ICGCS.2010.5543018.

[213] D. N. Perkins, M.-N. B. Drisse, T. Nxele, and P. D. Sly, "E-waste: A Global Hazard," *Annals of global health*, vol. 80, no. 4, pp. 286–295, 2014, https://doi.org/10.1016/j.aogh.2014.10.001.

[214] J. Halloy, N. Nova, and A. Monnin, "Au-delà du low tech," *Ritimo*, vol. 21, 2020. [Online]. Available: https://hal.science/hal-02950609

[215] A. Bjørn, M. Owsianiak, C. Molin, and M. Z. Hauschild, "LCA history," *Life cycle assessment: theory and practice*, pp. 17–30, 2018, https://doi.org/10.1007/978-3-319-56475-3_3.

[216] S. Sala, E. Crenna, M. Secchi, and E. Sanyé-Mengual, "Environmental sustainability of European production and consumption assessed against planetary boundaries," *Journal of Environmental Management*, vol. 269, p. 110686, 2020, https://doi.org/10.1016/j.jenvman.2020.110686.

[217] A. Moltesen and A. Bjørn, "LCA and Sustainability," *Life Cycle Assessment: Theory and Practice*, pp. 43–55, 2018.

[218] K. Hayashi, "Partitioning product footprint changes into yield and environmental improvement effects: toward life cycle assessment of agricultural system transitions," *The International Journal of Life Cycle Assessment*, pp. 1–13, 2022, https://doi.org/10.1007/s11367-022-02112-2.

[219] K. Raworth, *Doughnut economics: seven ways to think like a 21st-century economist*. Chelsea Green Publishing, 2017.

[220] L. Hilty, "Computing Efficiency, Sufficiency, and Self-sufficiency: A Model for Sustainability?" 2015, https://doi.org/10.5167/uzh-110766.

[221] A. Vishwanath, K. Hinton, R. W. Ayre, and R. S. Tucker, "Modeling energy consumption in high-capacity routers and switches," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 8, pp. 1524–1532, 2014, http://dx.doi.org/10.1109/JSAC.2014.2335312.

[222] A. Borning, B. Friedman, and D. Gruen, "What pushes back from considering materiality in IT?" in *Proceedings of the 2018 Workshop on Computing within Limits*, 2018, pp. 1–6, https://doi.org/10.1145/3232617.3232627.

[223] W. Holt, "Moore's law: A path going forward," in *Proc. IEEE ISSCC*, 2016, pp. 8–13, https://doi.org/10.1109/ISSCC.2016.7417888.

[224] D. C. Brock and G. E. Moore, *Understanding Moore's law: four decades of innovation*. Chemical Heritage Foundation, 2006. [Online]. Available: https://www.sciencehistory.org/sites/default/files/understanding_moores_law.pdf

[225] C. Mack, "The multiple lives of Moore's law," *IEEE Spectrum*, vol. 52, no. 4, pp. 31–31, 2015. [Online]. Available: https://spectrum.ieee.org/the-multiple-lives-of-moores-law

[226] L. Eeckhout, "Is Moore's law slowing down? What's next?" *IEEE Micro*, vol. 37, no. 04, pp. 4–5, 2017, https://doi.org/10.1109/MM.2017.3211123.

[227] ——, "Kaya for Computer Architects: Toward Sustainable Computer Systems," *IEEE Micro*, vol. 43, no. 1, pp. 9–18, 2022. [Online]. Available: https://doi.org/10.1109/MM.2022.3218034

[228] S-C Hu and Y.K. Chuah, "Power consumption of semiconductor fabs in Taiwan," *Energy*, vol. 28, no. 8, pp. 895–907, Jun. 2003, https://doi.org/10.1016/S0360-5442(03)00008-2.

[229] M. A. Yao, T. G. Higgs, M. J. Cullen, S. Stewart, and T. A. Brady, "Comparative assessment of life cycle assessment methods used for personal computers," *Environ. Sci. & Technol.*, vol. 44, no. 19, pp. 7335–7346, Aug. 2010, https://doi.org/10.1021/es903297k.

[230] A. Esser and F. Sensfuss, "Review of the default primary energy factor (PEF) reflecting the estimated average EU generation efficiency referred to in Annex IV of Directive 2012/27/EU," European Commission, 2016, [Online]. Available: https://energy.ec.europa.eu/review-default-primary-energy-factor-pef-reflecting-estimated-average-eu-generation-efficiency_en.

[231] Hiroshigo Goto, "GPU Die Size & Process Technology," 2016, [Online]. Available: https://pc.watch.impress.co.jp/img/pcw/docs/1143/278/gpudie.png.

[232] J. Chen and X. Ran, "Deep learning with edge computing: A review," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1655–1674, 2019, https://doi.org/10.1109/JPROC.2019.2921977.

[233] F. Liu, G. Tang, Y. Li, Z. Cai, X. Zhang, and T. Zhou, "A survey on edge computing systems and tools," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1537–1562, 2019, https://doi.org/10.1109/JPROC.2019.2920341.

[234] NVIDIA, "Jetson: Accelerating Next-Gen Edge AI and Robotics," 2023, [Online]. Available: https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/.

[235] L.-A. Ragnarsson, C. Rolin, S. Shamuilia, and E. Parton, "Vision paper: The green transition of the IC industry," 2022, [Online]. Available: https://www.imec-int.com/sites/default/files/2022-07/Whitepaper_SSTS_FINAL.pdf?utm_campaign=imec%20-%20whitepaper%20SSTS%20download%20-%202022%20&utm_medium=email&utm_source=eloqua.

[236] McKinsey & Company, "Keeping the semiconductor industry on the path to net zero," 2022, [Online]. Available: https:

//www.mckinsey.com/industries/semiconductors/our-insights/keeping-the-semiconductor-industry-on-the-path-to-net-zero#/.

[237] Greenpeace, "Invisible Emissions: A forecast of tech supply chain emissions and electricity consumption by 2030," 2023, [Online]. Available: https://www.greenpeace.org/static/planet4-japan-stateless/2023/04/620390b7-greenpeace_energy_consumption_report.pdf.

[238] IRDS, "International roadmap for devices and systems: executive summary," 2022, [Online]. Available: https://irds.ieee.org/images/files/pdf/2022/2022IRDS_ES.pdf.

[239] T. Santarius, J. C. Bieser, V. Frick, M. Höjer, M. Gossen, L. M. Hilty, E. Kern, J. Pohl, F. Rohde, and S. Lange, "Digital sufficiency: conceptual considerations for ICTs on a finite planet," *Ann. of Telecommun.*, pp. 1–19, May 2022, https://doi.org/10.1007/s12243-022-00914-x.

[240] European Commission, "Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the regions: A Chips Act for Europe," 2022, [Online]. Available: https://eur-lex.europa.eu/legal-content/en/TXT/PDF/?uri=COM:2022:45:FIN.

[241] J. Voas, N. Kshetri, and J. F. DeFranco, "Scarcity and Global Insecurity: The Semiconductor Shortage," *IT Professional*, vol. 23, no. 5, pp. 78–82, 2021, https://doi.org/10.1109/MITP.2021.3105248.

[242] ACM Europe Technology Policy Committee, "Comments on the proposal for a regulation establishing a framework of measures for strengthening Europe's semiconductor ecosystem," 2022, [Online]. Available: https://europe.acm.org/binaries/content/assets/public-policy/europetpc-chips-act-comments-09may22.pdf.

[243] S. E. Bibri, "The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability," *Sustainable cities and society*, vol. 38, pp. 230–253, 2018, https://doi.org/10.1016/j.scs.2017.12.034.

[244] F. Bordage, "GreenIT.fr: The environmental footprint of the digital world," 2019, [Online]. Available: https://www.greenit.fr.

[245] IoT Analytics (K. L. Lueth), "Global number of IoT devices," 2020, [Online]. Available: https://iot-analytics.com/state-of-the-iot-2020-12-billion-iot-connections-surpassing-non-iot-for-the-first-time/.

[246] GSMA, "The Mobile Economy 2020," 2020, [Online]. Available: https://www.gsma.com/mobileeconomy/wp-content/uploads/2020/03/GSMA_MobileEconomy2020_Global.pdf.

[247] J. Malmodin, P. Bergmark, and D. Lundén, “The future carbon footprint of the ICT and E&M sectors,” *on Information and Communication Technologies*, p. 12, 2013, http://2013.ict4s.org/wp-content/uploads/paper/Malmodin_et_al_Future_Carbon_Footprint_of_ICT_and_E&M_Sectors.pdf.

[248] T. Adegbija, A. Rogacs, C. Patel, and A. Gordon-Ross, “Microprocessor optimizations for the internet of things: A survey,” *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 37, no. 1, pp. 7–20, 2017, https://doi.org/10.1109/TCAD.2017.2717782.

[249] E. Eriksson and D. Pargman, “Meeting the future in the past-using counterfactual history to imagine computing futures,” in *Proceedings of the 2018 Workshop on Computing within Limits*, 2018, pp. 1–8, https://doi.org/10.1145/3232617.3232621.

[250] S. Inayatullah, “Futures studies: theories and methods,” *There’sa future: Visions for a better world*, vol. 30, 2013. [Online]. Available: https://www.meta-future.org/uploads/7/7/3/2/7732993/futures_studies_theories_and_methods_published_version_2013_with_pics.pdf

[251] E. Fauré, Y. Arushanyan, E. Ekener, S. Miliutenko, and G. Finnveden, “Methods for assessing future scenarios from a sustainability perspective,” *European Journal of Futures Research*, vol. 5, no. 1, pp. 1–20, 2017, https://doi.org/10.1007/s40309-017-0121-9.

[252] L. Börjeson, M. Höjer, K.-H. Dreborg, T. Ekvall, and G. Finnveden, “Scenario types and techniques: towards a user’s guide,” *Futures*, vol. 38, no. 7, pp. 723–739, 2006, https://doi.org/10.1016/j.futures.2005.12.002.

[253] J. B. Robinson, “Futures under glass: a recipe for people who hate to predict,” *Futures*, vol. 22, no. 8, pp. 820–842, 1990, https://doi.org/10.1016/0016-3287(90)90018-D.

[254] ——, “Energy backcasting A proposed method of policy analysis,” *Energy policy*, vol. 10, no. 4, pp. 337–344, 1982, https://doi.org/10.1016/0301-4215(82)90048-9.

[255] K. H. Dreborg, “Essence of backcasting,” *Futures*, vol. 28, no. 9, pp. 813–828, 1996, https://doi.org/10.1016/S0016-3287(96)00044-4.

[256] S. E. Bibri, “A methodological framework for futures studies: integrating normative backcasting approaches and descriptive case study design for strategic data-driven smart sustainable city planning,” *Energy Informatics*, vol. 3, pp. 1–42, 2020, https://doi.org/10.1186/s42162-020-00133-5.

[257] M. Höjer and L.-G. Mattsson, “Determinism and backcasting in future studies,” *Futures*, vol. 32, no. 7, pp. 613–634, 2000, https://doi.org/10.1016/S0016-3287(00)00012-4.

[258] A. Ebolor, "Backcasting frugally innovative smart sustainable future cities," *Journal of Cleaner Production*, vol. 383, p. 135300, 2023, https://doi.org/10.1016/j.jclepro.2022.135300.

[259] A. Miola *et al.*, *Backcasting approach for sustainable mobility*, 2008, https://publications.jrc.ec.europa.eu/repository/handle/JRC45824.

[260] J. M. F. Mendoza, M. Sharmina, A. Gallego-Schmid, G. Heyes, and A. Azapagic, "Integrating backcasting and eco-design for the circular economy: The BECE framework," *Journal of Industrial Ecology*, vol. 21, no. 3, pp. 526–544, 2017, https://doi.org/10.1111/jiec.12590.

[261] S. E. Bibri and J. Krogstie, "Smart sustainable cities of the future: An extensive interdisciplinary literature review," *Sustainable cities and society*, vol. 31, pp. 183–212, 2017, https://doi.org/10.1016/j.scs.2017.02.016.

[262] ——, "Generating a vision for smart sustainable cities of the future: a scholarly backcasting approach," *European Journal of Futures Research*, vol. 7, pp. 1–20, 2019, https://doi.org/10.1186/s40309-019-0157-0.

[263] ——, "Environmentally data-driven smart sustainable cities: Applied innovative solutions for energy efficiency, pollution reduction, and urban metabolism," *Energy Informatics*, vol. 3, pp. 1–59, 2020, https://doi.org/10.1186/s42162-020-00130-8.

[264] S. E. Bibri, "Data-driven smart eco-cities and sustainable integrated districts: A best-evidence synthesis approach to an extensive literature review," *European Journal of Futures Research*, vol. 9, no. 1, pp. 1–43, 2021, https://doi.org/10.1186/s40309-019-0157-0.

[265] ——, "A novel model for data-driven smart sustainable cities of the future: the institutional transformations required for balancing and advancing the three goals of sustainability," *Energy Informatics*, vol. 4, pp. 1–37, 2021, https://doi.org/10.1186/s42162-021-00138-8.

[266] F. Cugurullo, "Exposing smart cities and eco-cities: Frankenstein urbanism and the sustainability challenges of the experimental city," *Environment and Planning A: Economy and Space*, vol. 50, no. 1, pp. 73–92, 2018, https://doi.org/10.1177/0308518X17738535.

[267] Agence de la Transition Energétique (ADEME), "Transitions 2050 – Rapport," 2021, [Online]. Available: https://librairie.ademe.fr/recherche-et-innovation/5072-prospective-transitions-2050-rapport.html.

[268] Wilson, Charlie, "1.5 °C Compatibility Pathfinder Framework (CPF)," 2019, [Online]. Available: https://silci.org/wp-content/uploads/Outputs/3a_Reports/2019-11_Wilson_MissionInnovation-report_1.5C-Compability.pdf.

[269] R. Sisto, E. Sica, and G. M. Cappelletti, "Drafting the strategy for sustainability in universities: A backcasting approach," *Sustainability*, vol. 12, no. 10, p. 4288, 2020, https://doi.org/10.3390/su12104288.

[270] R. Sisto, A. Lopolito, and M. Van Vliet, "Stakeholder participation in planning rural development strategies: Using backcasting to support Local Action Groups in complying with CLLD requirements," *Land use policy*, vol. 70, pp. 442–450, 2018, https://doi.org/10.1016/j.landusepol.2017.11.022.

[271] International Telecommunication Union (ITU), "Recommendation ITU-T L.1450: Methodologies for the assessment of the environmental impact of the information and communication technology sector," 2018, [Online]. Available: https://www.itu.int/rec/T-REC-L.1450.

[272] V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. Gomis *et al.*, "Climate change 2021: the physical science basis," *Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*, vol. 2, 2021. [Online]. Available: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FrontMatter.pdf

[273] Gouvernement Wallon, "Plan Air Climat Energie (PACE) 2030 de la Wallonie," 2023, [Online]. Available: https://awac.be/wp-content/uploads/2023/03/PACE-2030_adopte-GW-21-mars-2023.pdf.

[274] A. W. Hjalsted, A. Laurent, M. M. Andersen, K. H. Olsen, M. Ryberg, and M. Hauschild, "Sharing the safe operating space: Exploring ethical allocation principles to operationalize the planetary boundaries and assess absolute sustainability at individual and industrial sector levels," *Journal of Industrial Ecology*, vol. 25, no. 1, pp. 6–19, 2021, https://doi.org/10.1111/jiec.13050.

[275] Union des villes et des communes de Wallonie, "L'éclairage public," 2022, [Online]. Available: https://www.uvcw.be/energie/focus/art-2295.

[276] Parlement wallon, "Bilan énergétique de la Wallonie 2019 – Bilan du secteur domestique et équivalents – Version 2," 2022, [Online]. Available: https://energie.wallonie.be/servlet/Repository/bilan-domestique-et-equivalents-2019-v2.pdf?ID=67309.

[277] Our World In Data, "Carbon intensity of electricity, 2000 to 2022," 2022, [Online]. Available: https://ourworldindata.org/grapher/carbon-intensity-electricity?tab=chart&country=~BEL.

[278] Gouvernement belge, "Plan National Energie Climat Belge 2021-2023 (PNEC)," 2019, [Online]. Available: https://climat.be/doc/pnec-version-definitive.pdf.

[279] Moustique (K. Dupont), "Wallonie: la carte des communes qui éteindront leur éclairage public à partir de ce 1er Novembre," 2022.

[280] G. Pasolini, P. Toppan, F. Zabini, C. De Castro, and O. Andrisano, "Design, deployment and evolution of heterogeneous smart public lighting systems," *Applied Sciences*, vol. 9, no. 16, p. 3281, 2019, https://doi.org/10.3390/app91632816.

[281] World Business Council for Sustainable Development (WBCSD) and Net Zero Initiative, "Guidance on Avoided Emissions: Helping business drive innovations and scale solutions toward Net Zero," 2023, [Online]. Available: https://www.wbcsd.org/contentwbc/download/15909/229494/1.

[282] J. Druschke, S. Fath, L. Stobbe, N. F. Nissen, N. Richter, and K.-D. Lang, "Ecological Cost-Benefit Analysis of a Sensor-Based Parking Prediction Service," *EcoDesign and Sustainability II: Social Perspectives and Sustainability Assessment*, pp. 399–414, 2021, https://doi.org/10.1007/978-981-15-6775-9_26.

[283] G. Tress, B. Tress, and G. Fry, "Clarifying integrative research concepts in landscape ecology," *Landscape ecology*, vol. 20, pp. 479–493, 2005, https://doi.org/10.1007/s10980-004-3290-4.

[284] L. Bornes, "A Methodology and a Tool to Support the Sustainable Design of Interactive Systems: Adapting systemic design tools to model complexity in interaction design," in *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, 2023, pp. 1–5, https://doi.org/10.1145/3544549.3577055.

[285] G. Fourez, P. Mathy, and V. Englebert-lecomte, "Un modèle pour un travail interdisciplinaire," *Aster: Recherches en didactique des sciences expérimentales*, vol. 17, no. 1, pp. 119–142, 1993, https://www.persee.fr/doc/aster_0297-9373_1993_num_17_1_1328.

[286] imec, "imec.netzero – The imec virtual fab webapp," 2023, [Online]. Available: https://netzero.imec-int.com/.

[287] J. Marx, A. Schreiber, P. Zapp, and F. Walachowicz, "Comparative life cycle assessment of NdFeB permanent magnet production from different rare earth deposits," *ACS sustainable chemistry & engineering*, vol. 6, no. 5, pp. 5858–5867, 2018, https://doi.org/10.1021/acssuschemeng.7b04165.

[288] N. Lethaby, "Wireless connectivity for the Internet of Things: One size does not fit all," *Texas Instruments*, pp. 2–10, 2017, https://www.ti.com/lit/wp/swry010a/swry010a.pdf.

[289] Fraunhofer IZM, Fraunhofer ISI, VITO, "Ecodesign preparatory study on mobile phones, smartphones and tablets : Final Task 4 Report - Technologies," 2021, [Online]. Available: https://www.ecosmartphones.info/documents/.

[290] Cynel, "SAC305 Solder Paste," 2020, [Online]. Available: https://www.cynel.com.pl/en/products/103-sn96-5ag3cu0-5-sac305).

[291] P. Aryan, S. Sampath, and H. Sohn, "An overview of non-destructive testing methods for integrated circuit packaging inspection," *Sensors*, vol. 18, no. 7, p. 1981, 2018, https://doi.org/10.3390/s18071981.

[292] S. Marty, "Méthodes pour extraire un circuit intégré," 2014, [Online]. Available: https://www.youtube.com/watch?v=Pi31cXdBsHs.

[293] F. Marino, F. Leccese, and S. Pizzuti, "Adaptive street lighting predictive control," *Energy Procedia*, vol. 111, pp. 790–799, 2017, https://doi.org/10.1016/j.egypro.2017.03.241.

Appendix

A Modeling details for the hardware profiles framework

The full supplementary material published with [JP1] can be found online at doi: 10.1016/j.jclepro.2021.128966.

The following sections provide details on the modeling carried out in Sphera LCA for each functional block and HSL. Known limitations regarding the modeling assumptions are also disclosed.

Actuators

Hardware specifications: this framework models three type of actuators. A relay, a vibration motor and a small DC motor. As none of them are available in the Sphera LCA database, custom models were developed as detailed in Table A.3. The Solid State Relay (SSR) is modeled using an LED, a power transistor and a $1mm^2$ CMOS control circuit. For both motors, we consider NdFeB magnet by scaling another entry of the Sphera LCA database i.e. a 2g speaker, see Section A for more details. In addition, we consider steel, copper, a small 2-layer PCB and a small driver for the vibration motor. Regarding the DC motor, we include copper for wiring and coils, steel and thermoplastic for the bearings and structural components. A small IC is also included as motor control and driver with power transistors.

Limitations: the very scarce information regarding material declaration for the actuators complicates proper modeling. The presence of rare earths materials in the magnet needs more in-depth modeling and is likely to increase the footprint [287]. The modeling of relays could be extended to other types (e.g. electromechanical).

Casing

Hardware specifications: this framework models the casing as a mix of Acrylonitrile-Butadiene-Styrene Granulate (ABS) together with a process of plastic injection moulding supplied by the Chinese energy mix. Losses in the injection moulding process are considered up to 3%. Aluminium contribution is modeled by considering aluminium profiles produced through an extrusion process. Steel ingots model the presence of steel but no extrusion or casting process is considered. A ratio of 10-20-30% between aluminium-steel and plastic is supposed based on a rough analysis of the data available in [137] even though this is far more variable in practice. The impact of material selection for the casing is discussed in [19].

Limitations: casings with an important share of metals, heterogeneous materials, and processes need more in-depth modeling. The framework did not model hardware sunk in resin for outdoor nodes (waterproof), which is a common practice. Note that this significantly complicates the recycling of nodes.

Connectivity

Hardware specifications: this framework models connectivity hardware based on an equivalent silicon die area through CMOS 90 nm or 22 nm technology node. PCB printed antennas are considered to be part of the PCB *functional block*. For external antenna, we use a basic custom model based on a mix (20-40-40%) of copper, steel and ABS to model a 15g whip-like antenna. Regarding connectivity, some protocols or network architectures need a gateway for proper operation. This can be taken into account by considering the gateway as an IoT edge device and applying this framework to the gateway itself, thereby allocating its own impacts to the IoT edge devices that use it. Note that in Table 1 in the manuscript, the lowest hardware specification level (HSL-0) has connectivity capabilities directly embedded in the Processing *functional block*, such as in a wireless microcontroller with embedded radio transceiver.

Limitations: die inspections and statistical analysis are needed for communication ICs because literature and LCA databases are very scarce for communication devices [139]. To the best of our knowledge, no data base tackles this issue. As connectivity is a critical and necessary feature for IoT edge devices, a more in-depth

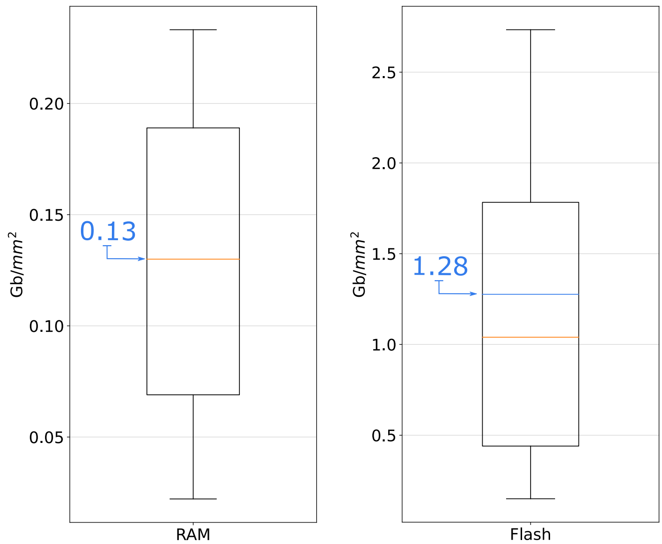

Fig. A.1 Boxplots for the memory trends over more than 10 years, RAM and Flash.

modeling would be valuable. Many protocols and technologies exist for IoT communication such as ZigBee, NB-IoT, LoRa, Bluetooth and WiFi [132, 288]. A better modeling of the wide range of antennas would also be of interest.

Memory

Hardware specifications: this relates only to stand-alone external memory ICs. A distinction between volatile (e.g DRAM) and non-volatile memory (e.g. Flash) is done. This framework models memory hardware based on an equivalent silicon die area and CMOS 45/57 nm technology node, for Flash and DRAM respectively. Memory density is considered when actual die size is not available: 0.13 Gb/mm^2 is used for (S/D)RAM and 1.28 Gb/mm^2 for Flash [289].

Limitations: the comparison of silicon area obtained from the thermal pad estimation and memory density trends (Gb/mm^2) over the last decades reveals a potential overshoot when thermal pad area is used as a proxy for die size. For this reason, memory density has been considered when no other information was available: 0.13 Gb/mm^2 has been used for (S/D)RAM and 1.28 Gb/mm^2 for Flash. Several sources have been analyzed with trends over more than 10 years (2010-2022). All details and sources are given in the memory_density_trends.xlsx file, please refer to the full supplementary material published with [JP1]. Figure A.1 shows two boxplots for the RAM and Flash densities across the different sources considered. These densities seem coherent with recent work [289] which evaluates about 0.22 Gb/mm^2 for DRAM and from 1.28 to 2.56 Gb/mm^2 for Flash. Nevertheless, they focus on smartphones only. The die-to-package ratios given in the Sphera LCA documentation suggest that stack dies are not taken into account nor memory capacity. This is problematic as it is more common for memory ICs to find stack dies in a single package. Stacked dies are usually thinner than non-stacked dies but total silicon die area is considerably increased, so are the environmental impacts. Die inspections and statistical analysis would be useful to better evaluate silicon die area in memory packages. Another limitation is that 45/57 nm are quite old technologies for memories but these are the only ones available in the Sphera LCA Electronics Extension database. Similarly, the type of package could be discussed but limited choice is available in Sphera LCA for memory ICs.

Printed circuit board (PCB)

Hardware specifications: this framework models PCB hardware based on area and number of layers, as suggested in ETSI and ITU standards [109, 72]. The solder paste used to fasten components to the PCB is also taken into account by considering SnAg3Cu0.5 (SAC) solder paste. The quantity is defined according to the total area of ICs, considering a thickness of $0.1mm$ and a mass density of $7.38g/cm^3$ [290]. As mentioned in the Sphera LCA documentation for rigid PCB with HASL finish, a subtractive method is considered with relevant process steps through a parametrized model, e.g., core preparation, layering, outer layer preparation, finishing and overheads. Assembly for through-hole technology (THT) and surface-mount device (SMD) components are also taken into account in Sphera LCA (600/h throughput).

Limitations: 4 to 8 routing metal layers are considered in this framework but for highly integrated designs, this could go above 10 layers which is not directly captured here. A reasonable conversion can be done by multiplying area and number of layers. Regarding the solder paste, it is a rough approximation.

Power supply

Hardware specifications: this framework models power supply hardware through coin cell, AA/AAA alkaline batteries or Li-ion batteries. Coin cell and AA/AAA alkaline batteries are taken directly from Sphera LCA. The emission factor for small alkaline batteries are similar between the Base Carbone and Sphera LCA. More specifically, Base Carbone gives 0.0653 kgCO_2eq/unit and 0.137 kgCO_2eq/unit for AAA and AA alkaline batteries while Sphera LCA gives below 0.1 kgCO_2eq and below 0.2 $kgCO_2eq$/unit, respectively. However, Sphera LCA does not contain Li-ion components. Results from another study [134] have been used as a proxy to model carbon footprint of Li-ion battery production. Their results were normalized by weight and capacity which is straightforward to scale. Carbon footprint is similar to [20] which used primary data but did not detail the life cycle inventory for the battery. In fact, 1.4 $kgCO_2eq$ for a 48g Li-ion battery gives 29.17 $kgCO_2eq$/kg, close to the 25 $kgCO_2eq$/kg from [134]. In [139], an emission factor of 29.62 $kgCO_2eq$/kg is used. Ecoinvent data for Li-ion battery ranges from 5.7 to 7.7 $kgCO_2eq$/kg but it is from 2011 and consequently outdated. The framework also takes into account a power management unit (PMU) for main-powered edge devices by considering basic AC/DC and DC/DC converters through coils, capacitors, power transistors and diodes. A power cord and a CEE 7/4 Schuko plug model are also considered. Some IoT edge devices use a dedicated PMU IC which is captured in HSL-3.

Limitations: energy harvesting is not covered by this framework. Even though it is increasingly used for industrial IoT applications, it is less the case for consumer IoT edge devices. Energy harvesting has the potential to extend the lifetime of the IoT edge devices and to decrease the need of maintenance but this comes at the expense of some additional hardware components, e.g., energy harvesters, supercapacitors and power management ICs. This trade-off should be considered in future works in regards of environmental impacts.

Processing

Hardware specifications: this framework models processing based on an equivalent silicon die area through CMOS 90nm technology node for microcontrollers (MCU) and CMOS 14nm for application processors. Common IoT edge devices often use Cortex-M MCUs and Cortex-A applications processors [248, 132]. Moreover, small embedded memory in the main MCU and processor is considered.

Limitations: die inspections and statisical analysis of several IoT processing ICs would help to better estimate the effective silicon die area and content of ICs. The type of package could be discussed but the priority was given to the technology node among the available database entries.

Security

Hardware specifications: this covers only external stand-alone security ICs. In practice, most IoT edge devices embed this function directly in the main MCU and processor, e.g., embedded AES encryption. This framework models security hardware based on an equivalent silicon die area and CMOS 90nm technology node.

Limitations: only small external security ICs are considered.

Sensing

Hardware specifications: this framework models sensors based on an equivalent silicon die area through CMOS $0.25\mu m$ technology node. For audio sensor, an electret condenser microphone from Sphera LCA is considered. For camera, only the CMOS sensor is modeled by an equivalent silicon die area in $0.13\mu m$ as it represents the main part of the impacts [164]: sensor area range from 1/4" to 2/3".

Limitations: common sensors are temperature, pressure and audio, proximity, inertial measurement unit, passive infrared sensors, GPS, image and video sensors. However, they usually use electro-chemical and non-CMOS technologies that are not captured by this framework.

Transport

Hardware specifications: transport is modeled based on chargeable weight as motivated in ETSI-ITU standards. It is assumed that the assembled IoT device is sent from China to Europe by a cargo plane (up to 65t payload) using EU-28 Kerosen Jet A1 and then transported by truck (Euro 4, up to 2.7t payload capacity) using EU-28 diesel mix to its destination in Europe.

Limitations: this is a simplified view of real world logistics which likely underestimates actual distances and the diversity in the modes of transportation.

User interfaces (UI)

Hardware specifications: this framework models user interfaces through switch buttons, LEDs, a speaker and an LCD display. For the display, panel size is ranging from $5cm^2$ to $100cm^2$. For the sake of comparison, a 2020 smartphone screen is about $80 - 90cm^2$. As Sphera LCA databases does not contain any display modules, modeling is done using primary data for touch screens [135], similarly to [139].

Push buttons and LEDs are taken from Sphera LCA. A small CMOS driver is considered for the LEDs. The original 2g speaker with neodymium selected in Sphera LCA is proportionally scaled up on a weight basis to cover heavier speakers: the resulting emission factor per kg seems coherent with other studies focusing on NdFeB magnets [287], respectively 57.3 $kgCO_2eq/kg$ compared to 33.5 $kgCO_2eq/kg$ in the Base Carbone and 41.4-89.2 $kgCO_2eq/kg$ in [287]. A small audio driver is also considered.

Limitations: large displays are not captured in this framework. Regarding GWP impacts, [19] points out that the impact of upstream suppliers and the production of input material is not covered in [135]. This might explain at least partially why the energy per m^2 of the Taiwanese display manufacturer is about one order of magnitude lower than in [20] i.e. 0.008 kWh/cm^2 compared to 0.1 kWh/cm^2, respectively.

Others

Hardware specifications: this includes capacitors, resistors, coils, crystal, additional transistors, electromagnetic shields (EMS) for ICs and cables.

Limitations: connectors are not covered (cut-off).

Parameters used for the modeling in Sphera LCA

Table A.1 and Table A.2 detail the plans parameters that are used in the LCA software, with respect to Table 2.2.

Table A.1 Plans parameters used for the framework modeling in the Sphera LCA software (part I).

Functional block	Part	HSL-0 low	HSL-0 typical	HSL-0 up	HSL-1 low	HSL-1 typical	HSL-1 up	HSL-2 low	HSL-2 typical	HSL-2 up	HSL-3 low	HSL-3 typical	HSL-3 up
Actuators	Piece of Vibration motor (1g)‡ [piece]	0	0	0	1	2	4	0	0	0	0	0	0
	Piece of Relay (SSR) ‡ [piece]	0	0	0	0	0	0	1	2	4	0	0	0
	Piece of DC motor ‡ [piece]	0	0	0	0	0	0	0	0	0	1	4	6
	Piece of transistor D2PAK TO263 (1.38g) 10.3x9.6x4.5 [piece]	0	0	0	0	0	0	0	0	0	1	4	6
	Piece of IC TQFP 32 (70mg) 5x5x1.0 [piece]	0	0	0	0	0	0	0	0	0	0.08	0.16	0.4
Casing	Plastic weight [kg]	0	0	0	0.01	0.05	0.1	0.2	0.4	0.5	0.7	0.8	0.9
	Aluminium weight [kg]	0	0	0	1×10^{-3}	0.01	0.03	0.02	0.08	0.15	0.07	0.16	0.3
	Steel weight [kg]	0	0	0	1×10^{-3}	0.01	0.03	0.02	0.08	0.15	0.07	0.16	0.3
Connectivity	Piece of IC QFP 32 (180mg) 7x7x1.5 [piece]	0	0	0	0.2	0.41	0.82	0	0	0	0	0	0
	Piece of WLP CSP 196 (400mg) (12x12x1.41mm) CMOS logic (22 nm node) [piece]	0	0	0	0	0	0	0.15	0.23	0.35	0.35	0.39	0.46
	Piece of external antenna‡ [piece]	0	0	0	0	0	0	0.66	1	2	0.66	1	2
Memory	Piece of IC TSSOP 16 (65mg) 4.4x5.0x1.2 [piece]	0	0	0	0	0	0	0	0	0	0	0	0
	Piece of IC TSSOP 16 (65mg) 4.4x5.0x1.2 (Flash) [piece]	0	0	0	0	0	0	0	0	0	0	0	0
	Piece of IC TSSOP 48 (102mg) 6.1x12.5x1.2 [piece]	0	0	0	8.8×10^{-2}	0.35	1.41	1.41	2.76	5.12	1.41	2.76	5.12
	Piece of IC TSSOP 48 (102mg) 6.1x12.5x1.2 (Flash) [piece]	0	0	0	9×10^{-3}	3.6×10^{-2}	0.14	0.28	1.12	2.24	2.24	4.48	8.96
Others	Piece of resistor flat chip 0402 (0.6mg) [piece]	5	10	15	15	20	25	40	50	60	75	85	100
	Piece of capacitor ceramic MLCC 0603 with precious metals (6mg) 1.6x0.8x0.8 [piece]	5	10	15	15	20	25	40	50	60	75	85	100
	Piece of diode signal DO214/219 (14.8mg) 3.9x1.9x1 [piece]	1	1	1	1	2	3	1	2	3	1	3	5
	Piece of diode signal SOD123/323/523 (9.26mg) 2.4x1.6x1 with Au-Bondwire [piece]	1	1	1	1	2	3	1	2	3	1	3	5
	Piece of capacitor tantal SMD Z (8mg) 2x1.25x1.2 [piece]	0	0	2	0	0	3	0	0	4	0	2	4
	Piece of capacitor ceramic MLCC 0603 with base metals (6mg) 1.6x0.8x0.8 [piece]	0	0	0	0	0	0	0	0	0	0	0	0
	Piece of oscillator crystal (500mg) 11.05x4.65x2.5 [piece]	0	1	1	1	1	2	1	2	4	1	2	4
	Piece of transistor signal SOT23 3 leads (10mg) 1.4x3x1 [piece]	1	2	3	2	4	6	4	7	9	7	10	15
	Mass of EMS shielding [kg]	0	0	0	5×10^{-4}	1×10^{-3}	2×10^{-3}	5×10^{-4}	1×10^{-3}	2×10^{-3}	5×10^{-4}	1×10^{-3}	2×10^{-3}
	Length of Cable 1-core signal [m]	0.01	0.02	0.05	0.01	0.02	0.05	0.02	0.05	0.08	0.05	0.08	0.1
PCB	Area of printed wiring board, rigid FR4, HASL, 8-layer [m^2]	0	0	0	0	0	0	3.5×10^{-3}	5×10^{-3}	0.01	8×10^{-3}	1.2×10^{-2}	1.5×10^{-2}
	Area of printed wiring board, rigid, FR4, HASL, 4-layer [m^2]	8×10^{-4}	1×10^{-3}	1.5×10^{-3}	1.5×10^{-3}	3.5×10^{-3}	5×10^{-3}	0	0	0	0	0	0
	Area of printed wiring board, rigid, FR4, HASL, 2-layer [m^2]	0	0	0	0	0	0	0	0	0	0	0	0
	Mass of solder paste SnPb36 [kg]	0	0	0	0	0	0	0	0	0	0	0	0
	Mass of solder paste SnAg3Cu0.5 (SAC-Lot) [kg]	4×10^{-6}	8×10^{-6}	1.2×10^{-5}	2.8×10^{-5}	5.3×10^{-5}	9.7×10^{-5}	9.9×10^{-5}	1.55×10^{-4}	2.49×10^{-4}	1.78×10^{-4}	2.65×10^{-4}	4.54×10^{-4}
(...)													

‡ custom modeling with Sphera LCA data.

Table A.2 Plans parameters used for the framework modeling in the Sphera LCA software (part II).

Functional block	Part	HSL-0 low	HSL-0 typical	HSL-0 up	HSL-1 low	HSL-1 typical	HSL-1 up	HSL-2 low	HSL-2 typical	HSL-2 up	HSL-3 low	HSL-3 typical	HSL-3 up
(...)													
Power Supply	Piece of Alkaline cell LR Series (AA) [piece]	0	0	0	0	0	2	0	0	0	0	0	0
	Piece of Alkaline cell LR Series (AAA) [piece]	0	0	0	0	2	0	0	0	0	0	0	0
	Piece of Cell BR Series (Li/Poly-carbonmonofluoride - RB0.8;RS0.65) [piece]	0	0	0	1	0	0	0	0	0	0	0	0
	Mass of Li-ion battery ▲ [kg]	0	0	0	0	0	0	0.01	0.05	0.1	0.01	0.05	0.1
	Piece of transistor DPAK TO252 (290mg) 6.6x6.2x2.2 [piece]	2	3	4	0	0	0	0	1	2	0	1	2
	Piece of Ring Core Coil 8g (With housing) [piece]	0	1	1	0	0	0	0	0	0	0	0	0
	Piece of coil miniature wound SDR0302 (81mg) D3x2.5 [piece]	2	3	4	0	0	0	0	1	2	0	1	2
	Piece of diode power DO214/219 (93mg) 4.3x3.6x2.3 [piece]	0	1	2	0	0	0	0	1	2	0	1	2
	Piece of capacitor Al-Elko radial THT (110mg) D3x5 [piece]	5	5	5	0	0	0	0	1	2	0	3	5
	Piece of IC BGA 48 (72mg) 8x6 mm MPU generic (130 nm node) [piece]	0	0	0	0	0	0	0	0	0	0.13	0.39	0.65
	Length of Cable 1-core power [m]	0.5	1	1.5	0	0	0	0	0	0	0	0	0
	Piece of schuko connector [piece]	0	1	1	0	0	0	0	0	0	0	0	0
Processing	Piece of IC QFP 32 (180mg) 7x7x1.5 [piece]	0.2	0.41	0.7	0.2	0.41	0.7	0.2	0.41	0.7	0.2	0.41	0.7
	Piece of WLP CSP 196 (400mg) 12x12x1.41mm CMOS logic (14 nm node) [piece]	0	0	0	0.15	0.23	0.34	0.39	0.46	0.58	0.58	0.77	0.96
Security	Piece of IC SO 8 (80mg) 4.9x3.9x1.7 [piece]	0	0	0	0.11	0.22	0.33	0	0	0	0	0	0
Sensing	Piece of IC DIP 8 (480mg) 10.9x6.6x3.3 [piece]	0	0	0	0	0	0	0	0.14	0.23	0	0.14	0.23
	Piece of IC TQFP 44 (260mg) 10x10x1.0 [piece]	0	0	0	0	0	0	0	0	0	0.154	0.6	1.16
	Piece of Microphone (0.05g, electret condenser, SMD) [piece]	0	0	0	1	2	4	0	0	0	0	0	0
Transport	Distance travelled by truck [km]	0	0	0	100	300	600	100	300	600	600	900	1200
	Distance travelled by plane [km]	0	0	0	6100	6775	7400	6100	6775	7400	6100	6775	7400
	Total weight [kg]	0	0	0	0.05	0.1	0.3	0.3	0.65	0.9	0.9	1.5	2
User interface	Piece of key switch Tact (242mg) 6.2x6.3x1.8 [piece]	0	0	0	0	1	2	0	2	3	2	3	4
	Piece of LED top SMD (35mg) 3.2x2.8x1.9 [piece]	0	0	0	1	2	4	2	4	6	3	5	8
	Piece of Loudspeaker (dynamic, Nd magnet) [piece]	0	0	0	0	0	0	1	5	20	0	0	0
	Area of Display △ [m^2]	0	0	0	0	0	0	0	0	0	5×10^{-4}	2.5×10^{-3}	0.01
	Piece of WLP CSP 49 (10.2mg) (3.17x3.17x0.55mm) MPU generic (130 nm node) [piece]	0	0	0	0	0	0	0.11	0.33	0.77	0	0.22	0.44

‡ custom modeling with Sphera LCA data. ▲ data from [134]. △ data from [135].

Table A.3 Modeling details for the custom models implemented in Sphera LCA.

Custom model	Part	Quantity
Vibration motor (1g)	Copper wire [kg]	1×10^{-4}
	Loudspeaker (dynamic, Nd magnet) [piece]	0.1
	Printed wiring board HASL 2-layer (subtractive method) [m^2]	8×10^{-5}
	Steel billet (St) [kg]	7×10^{-4}
	Transistor signal SOT23 3 leads (10mg) 1.4x3x1 [piece]	1
Relay (SSR)	IC SO 8 (76mg) 4.9x3.9 mm [piece]	0.1
	LED SMD low-efficiency max 50mA (35mg) wo. Au 3.2x2.8x1.9 [piece]	1
	Transistor D2PAK TO263 (1.38g) 10.3x9.6x4.5 [piece]	1
DC motor (50g)	Cobalt, refined [kg]	4.5×10^{-3}
	Copper wire [kg]	0.1
	Loudspeaker (dynamic, Nd magnet) [piece]	7.5
	Steel billet (St) [kg]	0.02
	TPU adhesive [kg]	5×10^{-3}
External antenna (15g)	Copper wire [kg]	3×10^{-3}
	Plastic part [kg]	6×10^{-3}
	Steel billet (St) [kg]	6×10^{-3}

B General approach for component selection in databases

This section gives additional details about the method used for the teardowns, the IC desencapsulation, and the general approach for component selection in databases that we followed in this thesis. As highlighted in both ETSI-ITU standards [109, 72] and literature [20, 139, 18], assessing the life-cycle impacts of ICT products is a complex task. Indeed, each device is made up from different electronic components and very few details regarding environmental impacts are publicly available. Consequently, we conducted teardowns to reduce the uncertainty on the hardware components in several IoT devices under study, e.g., the HUE occupancy sensor, the Google Home mini, and the IoT node and gateway for the smart public lighting solution.

All these teardowns were performed in-house with a similar procedure. First, we carefully dismantle the device in order to preserve all materials and parts. Then, we remove all electromagnetic shields to access ICs. The majority of ICs are desolder using a rework station. We then identify ICs when it is possible, based on the information available on the packages. Datasheets are gathered (when possible) and all ICs are measured and weighted using a Statorius balance (d = 0.1 mg). In order to obtain the exact die size for each ICs, we use a chemical die inspection method to disintegrate epoxy packages. Several inspection methods can be used [291] but they can be expensive and demanding in terms of infrastructures, e.g., X-ray and micro X-ray fluorescence spectrometry (micro-XRF). To simplify the process, we use a 98% sulfuric acid solution (H_2SO_4) while heating up to 240°C under a gas extractor, as detailed by DeusExSilicium in one of his online tutorial [292]. It generally takes from 3 to 15 minutes for the die to be completely freed from the package. We then clean the bare dies with an ultrasonic water bath and we weight them. Finally, we use an optic microscope with a camera to inspect the dies and measure the actual die size precisely. Unfortunately, it is usually not possible to identify the technology nodes due to the important number of dense routing layers and power rails. We eventually check for stacked dies. Let us mention that all this work may be avoided if the necessary information were available in the datasheets.

Once the hardware components are clearly identified with detailed BoMs, a model is implemented in the LCA software. To do so, best candidates are selected in the databases. However, this process is not trivial and uncertainty is inserted at this stage (e.g., model uncertainty, epistemological uncertainty, and mistakes) although it is almost never explicitly addressed. To the best of our knowledge, there is currently no official rules, guidelines, best practices, or algorithms providing a clear method to identify the bests database entries for a given hardware component. This is further complicated by the lack of data regarding the different hardware components and by the colossal diversity of components in the field of electronics and semiconductors. Therefore, we detail here how we proceed for in the case of IC.

The key features we use are, by order of importance: (i) the function of the IC (e.g. logic, memory), (ii) the technology node, (iii) the package type, (iv) the number of input-outputs (IO) pins, and (v) the package dimensions. However, such information are generally difficult to obtain based on the analysis of datasheets, especially for the technology node. In addition, as the die-to-package ratio [138] is never provided in datasheets, estimating the die area is further complicated. In practice, we scale the database entries according to the ratio of the good die areas. This is usually done based on the die-to-package ratio given in the Sphera LCA documentation and the targeted die size, which is obtained either by desencapsulation (leading to the lowest uncertainty) or by approximations, even if this leads to higher uncertainties given the important variability in die-to-package ratios [138]. For instance, die-to-package ratio estimates [138] can be used, or the area of the thermal pad[14]. All ICs in this thesis are modeled using the Sphera LCA Extension XI (Electronics) database which is based on their parametric IC model. Production yields [94] are considered and the model covers main production aspects: silicon wafer production, front-end (die manufacturing) and back-end (packaging) processing, production of gases, chemicals and materials, perfluocarbon (PFC) emissions, and facility impacts.

Let us mention that for each component, an appreciation is defined for the entry selection, based on our knowledge of the database. We use three qualitative levels, i.e., *proper* if the entry properly matches the component, *approximation* if the entry is similar to the component to be modeled but still not fully representative, or *not modeled* if it was not possible to model the component. This qualitative information adds more transparency on the quality of the modeling, similarly to a pedigree matrix.

[14]The thermal pad is the metallic backplate of the chip package.

C Data and assumptions supporting IC-related analyses

The extensive supplementary material published with [JP2] can be found on IEEE DataPort at doi:10.21227/bjaa-yy58.

The first objective of this supplementary material is to ensure transparency and repeatability of our work. Nevertheless, its second goal is to foster the community to challenge our review, and most importantly to build upon it to improve the understanding of environmental impacts for IC manufacturing. One single `.xlsx` file contains all data and assumptions (apart from Sphera LCA, for confidentiality reasons[15]). The `.xlsx` file is structured in sheets according to the following structure (sheet numbers are in brackets):

(1) Criteria
(2)-(4) Environmental Footprint data (GWP, Energy, Water)
(5) Parameters
(6)-(8) Commercial database details
(9) Foundries details
(10) ITRS details
(11) Worldwide production details
(12) Apple SoC details
(13) Literature review details
(14)-(37) Scientific literature details
(38)-(40) Others (supplementary)

In particular, criteria in sheet (1) are defined according to the ten features defined in Section 3.2.4. All details regarding the scientific literature review as illustrated in Fig. 3.2 are disclosed in sheet (13). Then, sheets (2)-(4), (6)-(8), and (9) gather all the information used to obtain Figs. 3.3, 3.4, 3.5. The data used to generate Fig. 3.6 are provided in sheets (11) and (38).

All the data and assumptions used for the historical analysis in Chapter 5 can also be found in this supplementary material in sheets (2)-(4) and (38)-(40), which have been used to generate Fig. 5.2. Figures 5.5 and 5.3 are based on the data provided in sheet (10) and (12), respectively.

[15] We have been authorized to report the data in Fig. 3.3 but we cannot report the exact quantitative values.

D Modeling details for the LCA of a real-life IoT solution

In this section, we provide more details regarding the modeling assumptions and the implementation of the life-cycle model for the smart public lighting IoT solution. However, all information cannot be disclosed for confidentiality reasons.

Life-cycle model

The top-level life-cycle model implementation in Sphera LCA is provided in Fig. D.1. Additional details for the production phase can be found in Fig. D.2 and in Tables D.1 and D.2. Yet, the complete BoMs for the gateway and the IoT node contains each more than 70 entries, with one entry representing a different type of component or module. As a module can also gather up to several tens of components, the comprehensive BoMs are very long. Table D.1 and Table D.2 hence provide highly simplified versions of the BoMs, structured according to the functional blocks classification to ease readability. Moreover, we could not share all details regarding the hardware implementation of the IoT node and the gateway due to confidentiality limitations. The implementation of the remain life-cycle phases in Sphera LCA are illustrated in Fig. D.3.

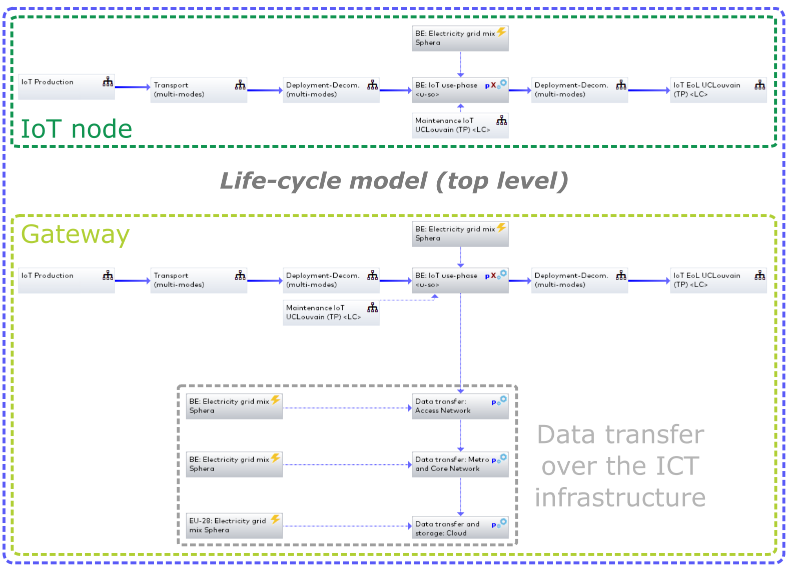

Fig. D.1 Implementation of the life-cycle model in Sphera LCA (top-level view).

Table D.1 Simplified bill of materials for the gateway.

Functional block	Components	Modeling based on ...	Physical quantity
Actuators			
	-	-	-
Casing			
	Housing	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.37 [kg]
	Screws, fasterners and nuts	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.22 [kg]
Connectivity			
	Bluetooth Low Energy Stand-alone (NINA-B301-00B)	In-depth custom modeling in Sphera LCA	1
	Wifi USB dongle (Edimax)	In-depth custom modeling in Sphera LCA	1
	Modem cellulaire PCIe (EG25GGB-MINIPCIE)	In-depth custom modeling in Sphera LCA	1
Memory			
	IC (Flash, microSD Card 16 GB)	"WLP CSP 196 (400mg) (12x12x1.41mm) flash (45 nm node)" in Sphera LCA	1
Others			
	Capacitors	"Capacitor ceramic MLCC 0603 with base metals (6mg) 1.6x0.8x0.8" in Sphera LCA	28
	Capacitors (Tantalum)	"Capacitor tantal SMD E (500mg) 7.3x4.3x4.1" in Sphera LCA	3
	Resistors	"Resistor flat chip 0402 (0.6mg)" in Sphera LCA	40
	Diodes	"Diode signal DO214/219 (14.8mg) 3.9x1.9x1" in Sphera LCA	2
	EMS shield	"EMS shielding" in Sphera LCA	0.003 [kg]
	Solder paste	"SnAg3Cu0.5 (SAC-Lot)" in Sphera LCA	0.000698 [kg]
	Fuses	**Not modeled**	2
	Connectors	**Not modeled**	7 (<10g)
PCB			
	Antenna Patch◁ GPS	"Printed wiring board, rigid, FR4, HASL, 2-layer"	0.00056 [m^2]
	Antenna Patch◁ 4G LTE	"Printed wiring board, rigid, FR4, HASL, 2-layer"	0.0016 [m^2]
	Main PCB◁	"Printed Wiring Board 4-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.0186 [m^2]
	Custom antenna PCB◁	"Printed Wiring Board 2-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.000182 [m^2]
Power supply			
	Toroidal choke	"Ring Core Coil 8g (Without housing)" in Sphera LCA	1
	ICs, LDO, and transistors	BGA, SOT, and D2PAK ICs in Sphera LCA	Several
Processing			
	Raspberry Pi (model B)	In-depth custom modeling in Sphera LCA	1
Security			
	-	-	-
Sensing			
	-	-	-
User Interface			
	LEDs	"Piece of LED top SMD (35mg) 3.2x2.8x1.9" in Sphera LCA	4
	Light pipe	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.000264 [kg]

◁ : Assembly line is taken into account in the life-cycle model.

Table D.2 Simplified bill of materials for the IoT node.

Functional block	Components	Modeling based on ...	Physical quantity
Actuators			
	-	-	-
Casing			
	Housing	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.051 [kg]
Connectivity			
	Bluetooth Low Energy Stand-alone (NINA-B301-00B)	In-depth custom modeling in Sphera LCA	1
	GPS Module, Ultra Compact (L80-M39)	In-depth custom modeling in Sphera LCA	1
Memory			
	IC (Flash)	"IC TSSOP 16 (59mg) 4.4x5.0 mm flash (45 nm node)" in Sphera LCA	1
Others			
	Capacitors	"Capacitor ceramic MLCC 0603 with base metals (6mg) 1.6x0.8x0.8" in Sphera LCA	36
	Resistors	"Resistor flat chip 0402 (0.6mg)" in Sphera LCA	47
	Inductors	"Coil multilayer chip 0402 (1mg) 1x0.5x0.5" (likely underestimated)	1
	Diodes	"Diode signal DO214/219 (14.8mg) 3.9x1.9x1" in Sphera LCA	3
	EMS shield	"EMS shielding" in Sphera LCA	0.0005 [kg]
	Solder paste	"SnAg3Cu0.5 (SAC-Lot)" in Sphera LCA	0.00014 [kg]
	Fuses	**Not modeled**	2
	Connectors	**Not modeled**	-
PCB			
	Main PCB◁	"Printed Wiring Board 4-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.0036 [m^2]
	Custom antenna PCB◁	"Printed Wiring Board 2-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.000182 [m^2]
Power supply			
	Diodes	"Diode power DO214/219 (93mg) 4.3x3.6x2.3"	2
	Power inductors	"Coil miniature wound SDR0302 (81mg) D3x2.5"	1
	ICs, LDO, and transistors	SOT ICs in Sphera LCA	Several
Processing			
	-	-	-
Security			
	-	-	-
Sensing			
	3-Axis Digital MEMS Accelerometer	"IC DIP 8 (538mg) 10.9x6.6 mm CMOS logic (250 nm node)" in Sphera LCA	1
	Lux meter	"IC DIP 8 (538mg) 10.9x6.6 mm CMOS logic (250 nm node)" in Sphera LCA	1
User Interface			
	LEDs	"LED top SMD (35mg) 3.2x2.8x1.9"	2
	LED	"Piece of LED top SMD (35mg) 3.2x2.8x1.9" in Sphera LCA	4
	Light pipe	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.000264 [kg]

◁: Assembly line is taken into account in the life-cycle model.

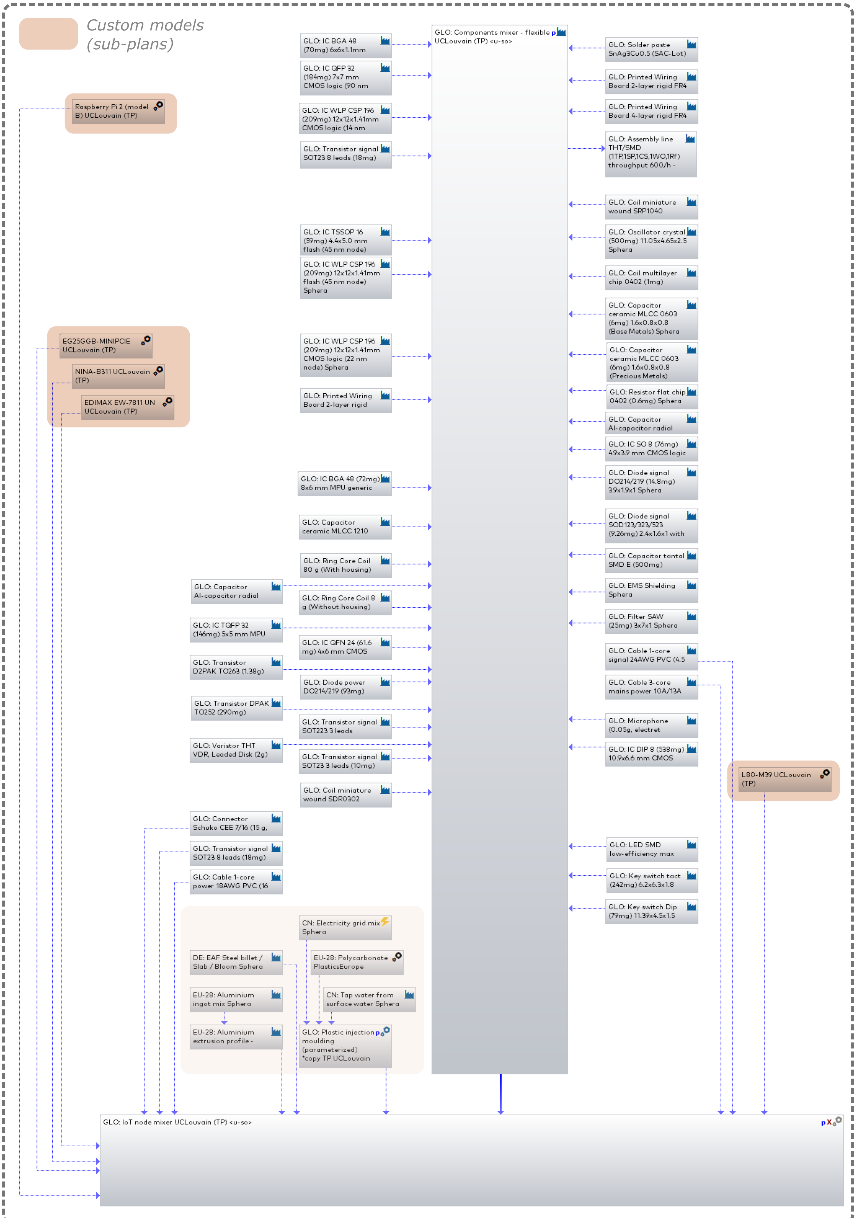

Fig. D.2 Implementation of the production phase in Sphera LCA. Custom models in sub-plans are not detailed here.

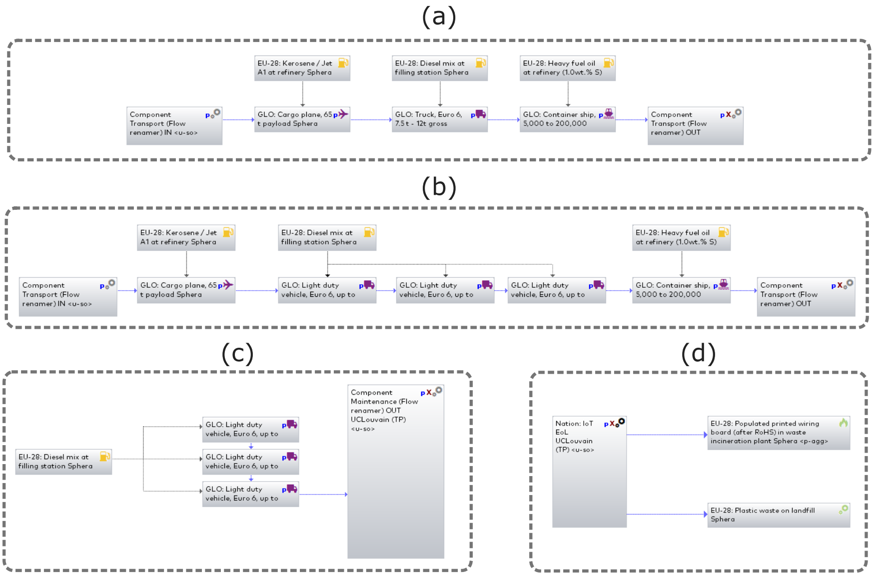

Fig. D.3 Implementation of other phases of the life cycle in Sphera LCA. (a) Transport. (b) Deployment and decommissioning. (c) Maintenance. (d) End of life.

Details supporting the literature review on the energy intensity of transferring data over the ICT infrastructure

Table D.3 and Table D.4 contain all the sources with the associated energy intensity considered in the literature review on the energy intensity of transferring data on the ICT infrastructure.

Table D.3 Identification of all relevant sources included in the literature review on energy intensity factors for transferring data on the ICT infrastructure, as illustrated in Fig. 4.3.

C1	C2	C3	C4	Included	Authors	Year	Methodology	Scope			kWh/GB available	Detailed model E/bit
								AN	MC	DC		
				✓	Andrae et al.	2015	Hybrid	✓	✗	✓	✓	✗
				✓	Aslan et al.	2017	Hybrid	✓	✓	✗	✓	✗
✓					Baliga et al.	2009	NA	NA	NA	NA	NA	NA
✓					Baliga et al.	2009	Bottom-up	NA	NA	NA	✗	✗
				✓	Baliga et al.	2011	Bottom-up	(✓)	✓	(✓)	✗	✓
	✓				Berl et al.	2010	NA	NA	NA	NA	NA	NA
		✓			Bianco et al.	2016	Bottom-up	✗	✗	✓	✗	✗
		✓			Boavizta	2022	Bottom-up	✗	✗	✓	✗	✗
				✓	Coroama and Hilty	2014	Hybrid	✓	✓	✗	✓	✗
				✓	Coroama et al.	2013	Bottom-up	✗	✓	✗	✓	✓
				✓	Golard et al.	2022	Bottom-up	✓	✗	✗	✓	✗
		✓			Hischier et al.	2014	Bottom-up	✓	✓	✓	✗	✗
	✓				Kumar et al.	2012	NA	NA	NA	NA	NA	NA
				✓	Malmodin et al.	2012	Hybrid	✗	✓	✗	✓	✗
		✓			Malmodin and Lunden	2016	Top-down	✓	✓	✓	✗	✗
				✓	Malmodin et al.	2014	Hybrid	✓	✓	✓	✓	✗
				✓	Malmodin et al.	2018	Top-down	✓	✓	✗	✓	✗
		✓			Masanet et al.	2020	Top-down	✗	✗	✓	✗	✗
				✓	Pihkola et al.	2018	Top-down	✓	✗	✗	✓	✗
				✓	Schien et al.	2013	Bottom-up	✓	✓	✗	✓	✗
				✓	Schien et Preist	2014	Bottom-up	✗	✓	✗	✓	✗
				✓	Teehan	2014	Top-down	✓	✓	✓	✓	✗
			✓		Ullrich et al.	2022	Bottom-up	✓	✓	✓	✗	✓
			✓		Vishwanath et al.	2014	Bottom-up	✗	✓	✗	✗	✓
			✓		Vishwanath et al.	2015	Bottom-up	✓	✓	✓	✗	✓
		✓			Williams et al.	2012	Bottom-up	✓	✓	✓	✗	✗
		✓			William and Tang	2013	Bottom-up	✓	✓	✓	✗	✗
✓					Koomey et al.	2004	-	-	-	-	-	-
✓					Taylor and Koomey	2008	-	-	-	-	-	-
✓					Pickavet et al.	2008	-	-	-	-	-	-
		✓			Weber et al.	2010	-	-	-	-	-	-
		✓			Lanzisera et al.	2012	-	-	-	-	-	-
		✓			Costenaro and Duer	2012	Hybrid	✓	✓	✓	✓	-
		✓			Shehabi et al.	2014	Extrapolation	-	-	-	-	-
		✓			Krug et al.	2014	Hybrid	-	-	-	-	-
			✓		Yan et al.	2019	Bottom-up	✓	✓	✓	✗	✓

C1: Not related to the period under study C2: Not retrieved C3: Not providing useful or original data
C4: Not providing data but insights for bottom-up modeling

Table D.4 Energy intensity factors for the studies included in the literature review, as shown in Fig. 4.4.

Source	Publication year	Reference year	Methodology	kWh/GB
Mobile Access network				
Andrae et al.	2015	2010	Hybrid	6
Andrae et al.	2015	2010	Hybrid	15
Andrae et al.	2015	2020	Hybrid	0.047
Andrae et al.	2015	2020	Hybrid	1.04
Pihkola et al.	2018	2016	Top-down	0.43
Pihkola et al.	2018	2017	Top-down	0.3
Pihkola et al.	2018	2020	Top-down	**0.1**
Golard et al.	2022	2020	Bottom-up	**0.27**
Golard et al.	2022	2025	Bottom-up	**0.15**
Malmodin et al.	2014	2010	Hybrid	2.9
Malmodin et al.	2014	2010	Hybrid	37
Malmodin et al.	2014	2007	Hybrid	7.6
Malmodin et al.	2014	2010	Hybrid	3.3
Malmodin et al.	2014	2015	Hybrid	0.88
Schien et al.	2013	2013	Bottom-up	0.03
Schien et al.	2013	2013	Bottom-up	0.12
Schien et al.	2013	2013	Bottom-up	0.293
Schien et al.	2013	2013	Bottom-up	0.73
Teehan	2014	2012	Top-down	6.7
Teehan	2014	2017	Top-down	0.7
Teehan	2014	2012	Top-down	3.7
Teehan	2014	2017	Top-down	0.4
Fixed Access network				
Andrae et al.	2015	2010	Hybrid	0.5
Andrae et al.	2015	2020	Hybrid	0.11
Andrae et al.	2015	2020	Hybrid	**0.28**
Andrae et al.	2015	2010	Hybrid	0.36
Andrae et al.	2015	2020	Hybrid	0.07
Andrae et al.	2015	2020	Hybrid	0.17
Malmodin et al.	2014	2010	Hybrid	0.08
Teehan	2014	2012	Top-down	**0.08**
Teehan	2014	2017	Top-down	0.05
Aslan et al.	2017	2015	Hybrid	0.06
Aslan et al.	2017	2019	Hybrid	**0.01**
Aslan et al.	2017	2015	Hybrid	0.023
Aslan et al.	2017	2011	Hybrid	0.7
Metro and Core network				
Malmodin et al.	2014	2010	Hybrid	0.08
Malmodin et al.	2014	2010	Hybrid	0.02
Malmodin et al.	2014	2012	Hybrid	**0.08**
Schien et al.	2013	2013	Bottom-up	0.01

... *(continue on the next page)* ...

Table D.4 Continued.

Source	**Publication year**	**Reference year**	**Methodology**	**kWh/GB**
...	*(continue from previous page)*		...	
Schien et al.	2013	2013	Bottom-up	0.023
Schien et al.	2013	2013	Bottom-up	0.08
Schien et Preist	2014	2014	Bottom-up	0.02
Schien et Preist	2014	2014	Bottom-up	0.0144
Schien et Preist	2014	2014	Bottom-up	0.023
Schien et Preist	2014	2014	Bottom-up	0.018
Schien et Preist	2014	2014	Bottom-up	0.39
Coroama et al.	2013	2009	Bottom-up	0.2
Aslan et al.	2017	2015	Hybrid	**0.06**
Aslan et al.	2017	2019	Hybrid	**0.01**
Aslan et al.	2017	2015	Hybrid	0.023
Aslan et al.	2017	2011	Hybrid	0.7
Teehan	2014	2013	Top-down	0.1
Baliga et al.	2011	2011	Bottom-up	0.006
Coroama and Hilty	2014	2008	Top-down	0.39
Coroama and Hilty	2014	2008	Top-down	1.8
Coroama and Hilty	2014	2007	Model-based	0.7
Coroama and Hilty	2014	2007	Model-based	2.1
Coroama and Hilty	2014	2009	Bottom-up	0.057
Data centers and clouds				
Andrae et al.	2015	2010	Hybrid	0.14
Andrae et al.	2015	2020	Hybrid	**0.027**
Andrae et al.	2015	2020	Hybrid	**0.085**
Malmodin et al.	2014	2010	Hybrid	1
Teehan	2014	2012	Top-down	0.32
Teehan	2014	2017	Top-down	**0.15**
Teehan	2014	2012	Top-down	0.08

Streamlined life cycle costing and eco-design

The LCA results suggest that the most effective way to reduce the direct effects of the IoT solution on indicators such as GWP and PED would be to reduce the use phase electricity consumption. However, this eco-design suggestion is in contradiction with the economic incentives for the vendor company. We therefore conducted a streamlined life cycle costing (LCC) to estimate the economic costs of the production and use phases of the IoT solution, as depicted in Fig. D.4. Yet, due to a lack of data for the other phases of the life cycle, only economic costs due to production and use phase have been considered with a bottom-up modeling. The economic costs associated with the deployment, the maintenance, the decommissioning phases or the mobile subscription for the gateway 4G connection should be included to cover the same scope as the LCA [51]. Nonetheless, this shows that the

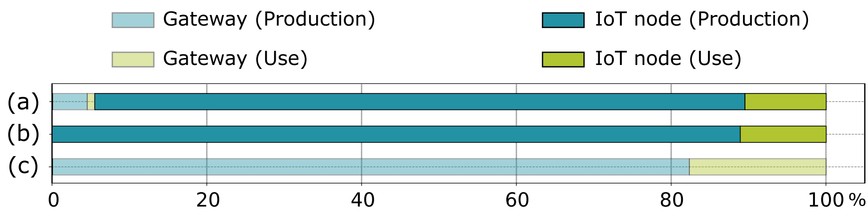

Fig. D.4 Streamlined life cycle costing results for (a) the full network as defined in the functional unit, (b) a single IoT node, and (c) a single gateway. Due to a lack of data on the entire life cycle, only economic costs due to production and use phase have been considered (bottom-up modeling).

economic costs mainly come from the production phase (more than 80%) whereas the environmental burden for indicators such as GWP and PED are clearly in the use phase, as detailed in the results interpretation. As the company is selling the IoT solution to an operator who is managing the network of streetlights, optimizing the use phase will increase the financial costs for the vendor company. On the contrary, the operator is not likely to complain about the electricity consumption of the IoT solution because it is much smaller than the expected energy savings per streetlight, as one lamp usually consumes between 80 and 120W. The company has therefore no direct economic incentive to reduce the environmental impacts of its current IoT solution. We also point out that the IoT solution under study is clearly a light-weight implementation of smart lighting, compared to real-time traffic counting solutions that embed edge-AI, cameras, and require heavier data transfer [293].

E Data for the macroscopic analysis on massive IoT deployment

Several market projections exist regarding the evolution of the number of IoT devices in the upcoming years [3, 1, 2, 244, 4, 245, 133, 246]. We focused on the ones from CISCO [3] and Statista [1] to model the massive deployment, as they seem to capture two main trends corroborated by the other sources. Extrapolation of the trends over a couple of years was done such that they all fit the same time frame, i.e., 2018-2028. While some trends are given in a cumulative number, others are given on a yearly basis. Because the carbon footprint of ICT is usually expressed in terms of $MtCO_2eq/year$, we converted cumulative trends to differential ones, when sufficient data were available. Tables E.1 and E.2 detail the trends for the different sources. According to Statista, this data does not include any computers, laptops, fixed line phones, cell phones or tablets. Active devices or gateways that concentrate the end-sensors are considered, but not every sensor-actuator. Table E.3 provides the values depicted in Fig. 6.1.

Table E.1 Cumulative number of IoT devices (billion), according to most popular market studies and predictions.

	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
CISCO	6.1	7.26	8.64	10.28	12.23	14.56	17.32†	20.61†	24.53†	29.19†	34.74†
Statista	23.14	27.4	32.43	38.4	45.46	53.82	63.72	75.44	89.31†	105.74†	125.19†
Gartner	N/A	14.5	N/A	25	N/A	N/A	N/A	N/A	N/A	N/A	N/A
IoT Analytics	8	10	11.7	13.8	16.4	19.8	24.4	30.9	N/A	N/A	N/A
GreenIT	N/A	N/A	20.315	N/A	N/A	N/A	N/A	48.272	N/A	N/A	N/A
IHS Markit◇	31	35	39	44	50	57	65	75	N/A	N/A	N/A
GSMA	N/A	12	N/A	N/A	N/A	N/A	N/A	24.6	N/A	N/A	N/A

†: personal extrapolation based on the previous trend. ◇: adapted from [133].

Table E.2 Yearly deployment of new IoT devices (billion) computed based on the trends in Table E.1.

	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
CISCO	1.16	1.38	1.64	1.95	2.33	2.76	3.29†	3.92†	4.66†	5.55†	N/A
Statista	4.26	5.03	5.97	7.06	8.36	9.9	11.72	13.87†	16.43†	19.45†	N/A
IoT Analytics	2	1.7	2.1	2.6	3.4	4.6	6.5	N/A	N/A	N/A	N/A
ARM	6	7.5	9	10.5	12	15	18	23	28	36	42
IHS Markit◇	4	4	5	6	7	8	10	N/A	N/A	N/A	N/A

†: personal extrapolation based on the previous trend. ◇: adapted from [133].

Table E.3 Macroscopic analysis of the annual carbon footprint generated by the production of IoT edge devices for different massive IoT deployment scenarios, in $MtCO_2eq$/year. SC stands for scenario. Bold values are the ones highlighted in the manuscript.

			2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
SC-1	CISCO$^{\blacktriangle}$	low	2.2	2.7	3.2	3.8	4.5	5.3	6.4	7.6	9.0	10.7
		typical	4.6	5.4	6.5	7.7	9.2	10.9	12.9	15.4	18.3	**21.8**
		up	6.9	8.2	9.7	11.6	13.8	16.4	19.5	23.3	27.7	33.0
	CISCO$^{\triangle}$	low	4.5	5.3	6.3	7.5	9.0	10.7	12.7	15.1	18.0	21.4
		typical	9.1	10.9	12.9	15.3	18.3	21.7	25.9	30.9	36.7	43.7
		up	13.8	16.4	19.5	23.2	27.7	32.8	39.1	46.6	55.3	65.9
	Statista$^{\blacktriangle}$	low	8.2	9.7	11.5	13.6	16.2	19.1	22.6	26.8	31.7	37.6
		typical	16.8	19.8	23.5	27.8	32.9	39.0	46.1	54.6	64.7	**76.5**
		up	25.3	29.9	35.4	41.9	49.6	58.8	69.6	82.4	97.6	115.5
	Statista$^{\triangle}$	low	16.5	19.4	23.1	27.3	32.3	38.3	45.3	53.6	63.5	75.2
		typical	33.5	39.6	47.0	55.6	65.8	77.9	92.2	109.2	129.3	**153.1**
		up	50.6	59.7	70.9	83.8	99.3	117.6	139.2	164.7	195.1	231.0
SC-2	CISCO$^{\blacktriangle}$	low	9.8	11.7	13.9	16.5	19.7	23.3	27.8	33.2	39.4	47.0
		typical	19.0	22.7	26.9	32.0	38.2	45.3	54.0	64.3	76.5	**91.1**
		up	28.3	33.6	40.0	47.5	56.8	67.3	80.2	95.5	113.6	135.3
	CISCO$^{\triangle}$	low	19.6	23.3	27.7	33.0	39.4	46.7	55.7	66.3	78.8	93.9
		typical	38.1	45.3	53.8	64.0	76.5	90.6	108.0	128.7	153.0	182.2
		up	56.5	67.3	79.9	95.0	113.6	134.5	160.4	191.1	227.1	270.5
	Statista$^{\blacktriangle}$	low	36.0	42.6	50.5	59.7	70.7	83.8	99.2	117.3	139.0	164.5
		typical	69.9	82.6	98.0	115.9	137.2	162.5	192.4	227.7	269.7	**319.3**
		up	103.8	122.6	145.5	172.1	203.7	241.3	285.6	338.0	400.4	474.0
	Statista$^{\triangle}$	low	72.1	85.1	101.0	119.5	141.5	167.5	198.3	234.7	278.0	329.1
		typical	139.9	165.1	196.0	231.8	274.5	325.0	384.8	455.4	539.4	**638.5**
		up	207.6	245.2	291.0	344.1	407.5	482.5	571.2	676.0	800.8	948.0
SC-3	CISCO$^{\blacktriangle}$	low	17.4	20.7	24.6	29.2	34.9	41.4	49.3	58.8	69.8	83.2
		typical	33.5	39.9	47.4	56.3	67.3	79.8	95.1	113.3	134.7	**160.4**
		up	49.7	59.1	70.2	83.5	99.7	118.1	140.8	167.8	199.5	237.6
	CISCO$^{\triangle}$	low	34.8	41.4	49.2	58.5	69.8	82.7	98.6	117.5	139.7	166.4
		typical	67.0	79.8	94.8	112.7	134.7	159.5	190.1	226.5	269.3	320.7
		up	99.3	118.1	140.4	166.9	199.5	236.3	281.6	335.6	398.9	475.1
	Statista$^{\blacktriangle}$	low	63.8	75.4	89.5	105.8	125.3	148.4	175.7	207.9	246.3	291.5
		typical	123.1	145.3	172.5	204.0	241.6	286.1	338.6	400.8	474.7	**562.0**
		up	182.3	215.3	255.5	302.2	357.8	423.7	501.6	593.7	703.2	832.5
	Statista$^{\triangle}$	low	127.7	150.8	179.0	211.6	250.6	296.8	351.3	415.8	492.5	583.0
		typical	246.2	290.7	345.0	408.0	483.1	572.1	677.3	801.5	949.5	**1124.0**
		up	364.7	430.6	511.1	604.4	715.6	847.5	1003.3	1187.3	1406.5	1665.0

$^{\blacktriangle}$ Framework baseline ($\psi = 1$). $^{\triangle}$ Framework revised upwards ($\psi = 2$).