

Generating energy transition pathways: application to Belgium

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*“A mes parents et grands parents”
qui m’ont tant donné,
sans rien attendre en retour.*

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Abstract

Humanity is at the beginning of its third energy revolution, after coal and then oil, we are now moving towards the massive use of renewable energies that we knew since the dawn of time. This change will solve several problems, including climate change, as the concentration of greenhouse gases will stabilise. The success of fossil fuels resides in their storability. Indeed, these energies have been stored in the earth for millions of years and can be extracted whenever humans need energy. Their costs of storage are insignificant compared to their costs of extraction. On the contrary, the main renewable energies are intermittent, i.e. wind and solar energy, and thus cannot be stored. However, these energy can be converted into electricity, heat or another form of energy that can be stored. But storing these energy carriers has a significant cost and thus, redefine the design of the energy system. Hence, the shift from fossil fuels to renewable energies - mainly intermittent - requires a complete rethinking of the energy system supply chain from resources to demand while including conversion and storage technologies. In particular, to understand what will be the role of storage technologies in this energy system throughout the energy transition period and after. To address this issue, the thesis addresses the following research question:

What is the role of energy storage technologies for the energy transition?

Focusing on the role of storage requires the inclusion of its environment, i.e. the energy system. Focusing on the energy transition requires a time horizon from today to about 2050. Thus, answering the research question requires a model that represents the energy system during the transition. These has motivated the following five contributions of the thesis. First, it is necessary to review the existing energy system models in the literature. Second, one of these models is improved to account for the complexities of energy storage. This involves, among others, to include different time scales (from hour to year) and to integrate all sectors of the energy system. Third, the model must be extended to the full time horizon, i.e. to enable the definition of the optimal pathway between today's energy system and the long-term goal. Fourth, the data for the case study must be collected and documented. And Fifth, as the proposed approach is deterministic (i.e. 'perfect foresight'), a method for accounting for uncertainty is proposed in order to qualify the results. The contributions as a whole provide a framework for generating several energy transition pathways. By applying it to Belgium, the framework offers an overview of the different strategies to reduce the

Abstract

greenhouse gas emissions, of the uncertain parameters that influence decision making, and of the different pathways to reach the long term-target. The whole-energy system approach enhances synergies among the different sectors, such as the importance of electrification. However, this approach cannot be extended to the whole system due to a limit on electricity production. The model prioritises the sectors that should benefit from electrification, such as low temperature heat. As a consequence, on the contrary to the current trends in the literature, private mobility is mainly supplemented by hydrogen vehicles. The reason is that hydrogen (or methane) is easier to import and store on a massive scale. By optimising several transition pathways, the main trends emerge: energy efficiency, local renewable energy, and finally, import of renewable fuels and electricity. Furthermore, an analysis of the overall transition shows the benefit of anticipating policy decisions such as the ban of technologies that are not compatible with a low emission system.

The energy transition will be one of the major challenges of the 21st century. With a profound change in the energy system and an integrated approach across sectors, this ambitious challenge can be overcome. Each country should contribute by maximising its cost-effective production of renewable energy before externalising the problem and unbalancing the efforts of other countries.

Keywords

Energy system modelling; Energy transition pathway; EnergyScope; Optimisation; Uncertainties.

Résumé

L'humanité est au début de sa troisième révolution énergétique, après le charbon puis le pétrole, nous nous dirigeons maintenant vers l'utilisation massive des énergies renouvelables que nous connaissons depuis la nuit des temps. Ce changement permettra de résoudre plusieurs problèmes, dont celui du changement climatique, puisque la concentration des gaz à effet de serre se stabilisera. Le succès des combustibles fossiles réside dans leur stockabilité. En effet, ces énergies sont stockées dans la terre depuis des millions d'années et peuvent être extraites dès que l'homme a besoin d'énergie. Leurs coûts de stockage sont minimes par rapport à leurs coûts d'extraction. En revanche, les principales énergies renouvelables sont intermittentes, à savoir l'énergie éolienne et l'énergie solaire, et ne peuvent donc pas être stockées. Cependant, ces énergies peuvent être converties en électricité, en chaleur ou en une autre forme d'énergie qui peut être stockée. Mais stocker ces vecteurs énergétiques a un coût important et redéfinit donc la structure du système énergétique. Par conséquent, le passage des combustibles fossiles aux énergies renouvelables - principalement intermittentes - nécessite de repenser entièrement la chaîne d'approvisionnement du système énergétique, des ressources à la demande, tout en incluant les technologies de conversion et de stockage. En particulier, il s'agit de comprendre quel sera le rôle des technologies de stockage dans ce système énergétique tout au long de la période de transition énergétique et après. Pour répondre à cette problématique, la thèse aborde la question de recherche suivante :

Quel est le rôle des technologies de stockage d'énergie pour la transition énergétique?

Se concentrer sur le rôle du stockage nécessite d'inclure son environnement, c'est-à-dire le système énergétique. Se concentrer sur la transition énergétique nécessite un horizon temporel allant d'aujourd'hui à environ 2050. Ainsi, pour répondre à la question de recherche, il faut un modèle qui représente le système énergétique pendant la transition.

Ces éléments ont motivé les cinq contributions suivantes de la thèse. Premièrement, il est nécessaire de passer en revue les modèles de système énergétique existants dans la littérature. Deuxièmement, l'un de ces modèles doit être amélioré pour prendre en compte les complexités du stockage énergétique. Cela implique, entre autres, d'inclure différentes échelles de temps (de l'heure à l'année) et d'intégrer tous les secteurs du système énergétique. Troisièmement, le modèle doit être étendu à l'horizon temporel complet, c'est-à-dire permettre la définition du chemin optimal entre le système

énergétique actuel et celui neutre en émission dans un futur proche. Quatrièmement, les données pour l'étude de cas doivent être collectées et documentées. Et cinquièmement, comme l'approche proposée est déterministe (c'est-à-dire une "prévision parfaite"), une méthode de prise en compte de l'incertitude est proposée afin de qualifier les résultats.

L'ensemble des contributions fournit une méthode permettant de générer plusieurs chemins de transition énergétique. En l'appliquant à la Belgique, la méthode offre une vue d'ensemble des différentes stratégies pour réduire les émissions de gaz à effet de serre à long terme, des paramètres incertains qui influencent la prise de décision et des différentes voies pour atteindre l'objectif à long terme. L'approche multi-énergies du système met en évidence les synergies entre les différents secteurs, comme l'importance de l'électrification. Toutefois, ce dernier exemple ne peut être étendue à l'ensemble du système en raison d'une limite de la production d'électricité. Ainsi, le modèle donne la priorité aux secteurs qui doivent bénéficier de l'électrification en premier, dont principalement la chaleur à basse température. En conséquence, contrairement aux tendances actuelles de la littérature, la mobilité privée est principalement complétée par des véhicules à hydrogène. L'origine de ce choix réside dans le fait que l'hydrogène (ou le méthane) est plus facile à importer et à stocker à grande échelle. En optimisant plusieurs voies de transition, les principales tendances émergent : l'efficacité énergétique, les énergies renouvelables locales, et enfin, l'importation de carburants et d'électricité renouvelables. En outre, l'analyse de la transition globale montre l'intérêt d'anticiper les décisions politiques telles que l'interdiction des technologies non compatibles avec un système à faibles émissions.

La transition énergétique sera l'un des grands défis du XXI^e siècle. Avec un changement profond du système énergétique et une approche intégrée dans tous les secteurs, ce défi ambitieux peut être surmonté. Chaque pays devrait contribuer en maximisant sa production rentable d'énergie renouvelable avant d'externaliser le problème et de déséquilibrer les efforts entre pays.

Mots-clefs

Modélisation de système énergétiques ; Chemin de transition ; EnergyScope ; Optimisation ; incertitudes.

Executive summary

Context and purpose of the thesis

By 2050, the European Union is committed to become climate neutral. This political commitment requires the energy system to be metamorphosed and drastically reduce its dependence on fossil fuels, the main sources of greenhouse gas emissions. A major debate confronts the different visions of the low-emission energy system, as well as the path to be adopted to reach this goal. Studies are regularly published on this subject, but the assumptions and models used are only partially shared, hindering the ability to challenge the work that has been done, or to update it. The objective of this work is to set up an open source methodology and to apply it to the case of Belgium.

Methodological approach

The methodology consists of three steps. First we seek to understand the different strategies of a low emission energy system. This involves answering questions such as: what is the role of storage technologies? Or, how to integrate intermittent renewable energies? The analysis of the different options reveals the most plausible low-emission energy system. Secondly, as the model is based on multiple projections of prices, availabilities, efficiencies, etc., we analyse the impact of the uncertainties on these parameters and identify the most critical ones, i.e. those that will influence the most the cost of the system. Thirdly, the transition path to reach the low emission target is optimised in order to have the road-map from today's system to tomorrow's low emission system.

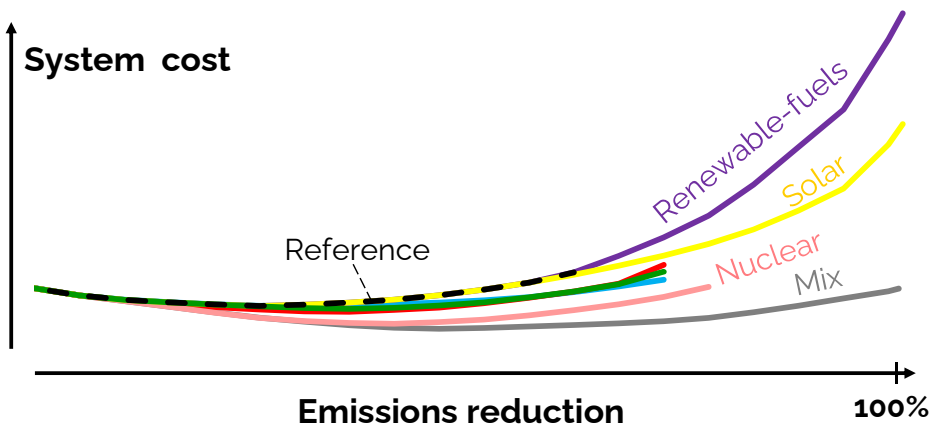
Main findings

A low emission energy system relies on a mix of solutions

In the case of Belgium, which can be partly transposed to several European countries, the optimal solution is a mix: massive deployment of endogenous renewable energy, implementation of efficient technologies, and if this is not enough, importing electricity and renewable fuels from abroad. Primary energy consumption can be reduced by 40% by using more efficient technologies, such as cogeneration, and coupling the energy sectors, mainly with electric mobility and heat pumps. Then, based on this reduced primary energy demand, 50% of it can be produced locally and based on renewable energies: 60 TWh/y of biomass, 60 TWh/y of solar and 35 TWh/y of wind. Finally, the remaining 50% will be imported renewable fuels and electricity from our neighbours. The

Executive summary

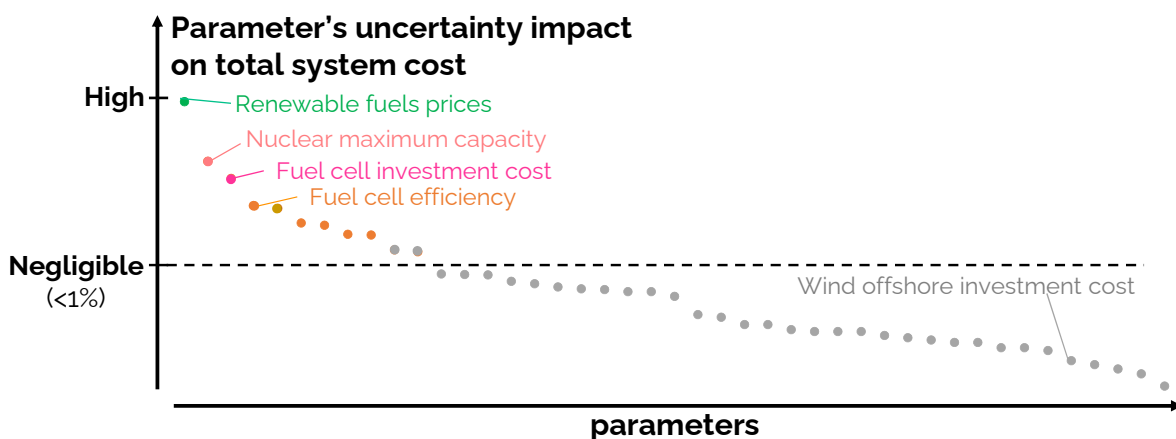
hypothetical use of additional renewables, such as geothermal energy or an extension of offshore wind farms, is beneficial to the system and reduces the dependence on foreign countries. These resources first need to be proven. The benefit of the mix is illustrated in the following figure where each curves represent a scenario with an abundant resource (i.e. above the expected potential):



On top of these scenarios, an additional one represents the extension of 2 GW of existing nuclear capacity.

Accounting for uncertainties qualifies the strategies

A global sensitivity analysis shows that, out of the hundreds uncertain parameters accounted, only a few of them are driving the uncertainty on the total cost of the system. The following figure illustrates the impact of each of the parameters on a low emission energy system in 2050:



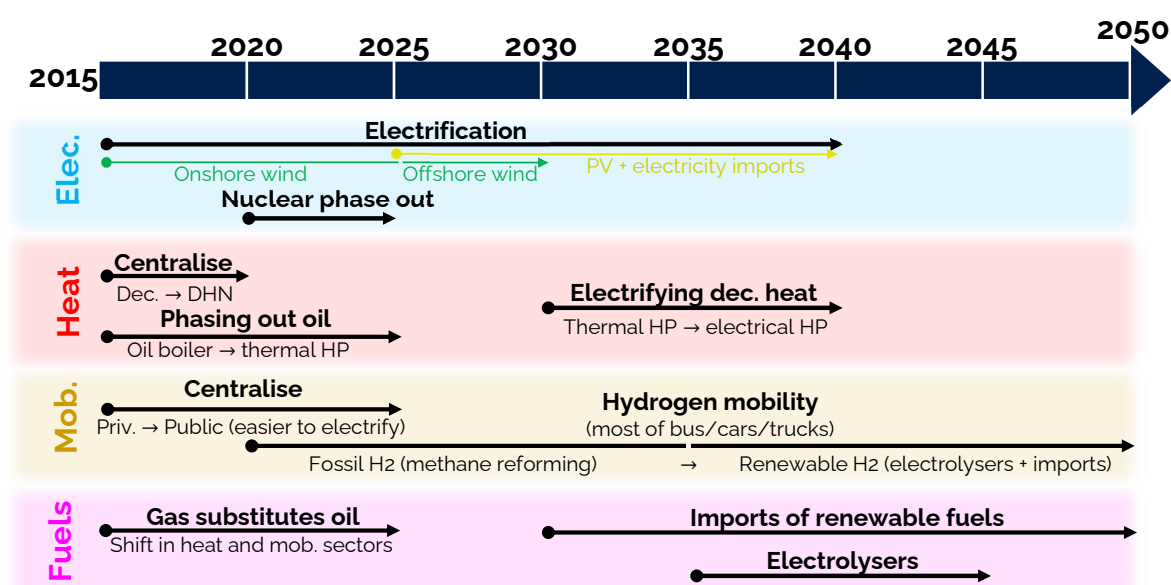
The y-axis is logarithmic which emphasises the dominant role of top parameters. From the top-4, three groups of parameters can be listed, by order of importance: the price of renewable fuels, the extension of nuclear power beyond 2025 and the fuel cells characteristics (price and efficiency). Renewable fuels include the transformation of biomass into fuel and also the use of excess renewable electricity to produce hydrogen and eventually more complex molecules. These fuels production

cost, and therefore their price, will be important. The uncertainty on their price changes the energy strategy: the highest the price, the highest the energy efficiency of the system. Today's nuclear power plants are amortised and if their safety can be proven, a partial extension will economically and technically facilitate the transition to a low-emission society. Finally, the fuel cells are used in vehicles and cogeneration. If their price is low and their efficiency high, most of the mobility (cars, buses, trucks) will rely on this technology. In addition, heat and electricity will be produced on a domestic scale through cogeneration with hydrogen or gas. But if fuel cells don't achieve this performance, then they may not appear in tomorrow's system.

To facilitate decision-making, the uncertainty about the total cost of the system must be reduced. This requires to focus on a dozen uncertain parameters. As an illustration, reducing the uncertainty on the top-4 parameters can reduce the system cost uncertainty by 80%. Others parameters' uncertainty, such as the one for the cost of wind power, will have limited influence on decision making because this technology will be deployed in all scenarios.

The transition pathway gives the road-map to follow

Optimising the transition pathway between 2015 and 2050 illustrates the priorities to be taken in each of the sectors and the efforts made in one sector to facilitate the integration of certain technologies into other sectors. As an example, the heat sector is strongly electrified and, as it can behave as a flexible electricity consumer, it facilitates the integration of intermittent renewables (solar and wind). Moreover, having a global view of the transition enables a sector to change progressively. For example, the transition to hydrogen mobility is progressive with hydrogen produced first from fossil fuels (steam reforming of natural gas) and then using renewable electricity (electrolysis) or imported. The following image represent, non-exhaustively, the decision taken in each sectors.



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Acronyms and abbreviations

A-EC	Alkaline electrolyser cell
AMPL	A mathematical programming language
BAU	Business-as-usual
BEV	Battery electric vehicle
CAPEX	Capital expenditure
CCGT	Combined cycle gas turbine
CCS	Carbon capture and storage
CEPCI	Chemical Engineering's Plant Cost Index
CHP	Cogeneration of heat and power
CNG	Compressed natural gas
CO ₂	Carbon dioxide
COP	Coefficient of performance
CRF	Capital recovery factor
DHN	District heating network
DME	Di-Methyl Ether
EC	European Commission
ECB	European central bank
EIA	Energy Information Administration
EnergyScope TD	EnergyScope Typical Days
ENTSOE	European Network of Transmission System Operators for Electricity
EROI	Energy return on investment
EU	European Union
EUD	End-use demand
EUT	End-use type
EV	Electric vehicle
FC	Fuel cell
FEC	Final energy consumption
FPB	Federal Planning Bureau
GDP	Gross domestic product
GHG	Greenhouse gas

Acronyms and abbreviations

GSA	Global sensitivity analysis
GWP	Global warming potential
H ₂	Hydrogen
HDD	Heat degree days
HDH	Heat degree hours
HEV	Hybrid electric vehicle
HP	Heat pump
HW	Hot water
IEA	International Energy Agency
IGCC	Integrated gasification combined cycle
IPCC	Intergovernmental Panel on Climate Change
IRM	Institut royal météorologique
JRC	Joint Research Center
KPI	Key performance indicator
LCA	Life cycle assessment
LCOE	Levelised cost of electricity
LFO	Light fuel oil
LHV	Lower heating value
LIFO	Last in first out
LP	Linear programming
MILP	Mixed-integer linear programming
MOB	Mobility
MOEA	Multi-objective evolutionary algorithm
MSW	Municipal solid waste
NG	Natural gas
NTC	Net transfer capacity
O&M	Operation and maintenance
Openmod	Open Energy Modelling Initiative
OPEX	Operational expenditure
ORC	Organic Rankine cycle
PCE	Polynomial chaos expansion
PDF	Probability density function
PEM-EC	Proton exchanger membrane electrolyser cell
PHEV	Plug-in hybrid electric vehicle
PHS	Pumped hydro storage
PtG	Power to gas
PtH	Power to heat
PV	Photovoltaic

RDO	Robust design optimisation
RE	Renewable energy
SH	Space heating
SLF	Synthetic liquid fuel
SMR	Steam methane reforming
SNG	Synthetic natural gas
SO-EC	Solid oxide electrolyser cell
SPF	Service public fédéral
TCO	Total cost of ownership
TD	Typical day
TS	Thermal storage
TSO	Transmission system operator
TTC	Total transfer capacity
TYNDP	Ten-Year Network Development Plan
U-S	Ultra-supercritical
V2G	Vehicle-to-grid
VITO	Vlaamse Instelling voor Technologisch Onderzoek

List of publications

First part of Chapter 1 is built on an opinion published in a journal:

Contino, F., Moret, S., Limpens, G., & Jeanmart, H. (2020). “*Whole-energy system models: The advisors for the energy transition.*” In *Progress in Energy and Combustion Science*, (Vol. 81). URL: <https://doi.org/10.1016/j.pecs.2020.100872>

The second part of Chapter 1 and the methodology presented in Chapter 2 are based on the peer-reviewed journal publication:

Limpens, G., Moret, S., Jeanmart, H., & Maréchal, F. (2019). “*EnergyScope TD: A novel open-source model for regional energy systems.*” In *Applied Energy*, (Vol. 255). URL: <https://doi.org/10.1016/j.apenergy.2019.113729>

The code used is documented and available on the following repository:

Limpens G. “*v2.1 Updated version of EnergyScope TD for Belgian application*”. URL: <https://github.com/energyscope/EnergyScope/tree/v2.1>

Chapters 4 and 5 are an extension of the case study and analysis performed, respectively, presented in an open-access and peer-reviewed journal publication:

Limpens, G., Jeanmart, H., & Maréchal, F. (2020). “*Belgian Energy Transition: What Are the Options?.*” In *Energies*, (Vol. 13, P. 261). URL <https://doi.org/10.3390/en13010261>

Chapter 6 is an extension of a peer-reviewed conference proceedings publication:

Limpens, G., Coppitters, D., Rixhon, X., Contino, F., & Jeanmart, H. (2020). “*The impact of uncertainties on the Belgian energy system: application of the Polynomial Chaos Expansion to the EnergyScope model.*” In *proceedings of ECOS 2020 conference* (Vol. 33, p. 711).

Chapters 3 and 7 related to the Pathway methodology and analysis are not published yet. However the code is documented and available on its repository:

List of publications

Limpens G. “*Pathway extension of model EnergyScope TD.*” URL: https://github.com/energyscope/EnergyScope_pathway

The following have not been presented in this thesis.

In a peer-reviewed journal paper, we proposed a terminology and classification for the fuels used during the energy transition and after:

Rixhon, X., Limpens, G., Contino, F., & Jeanmart, H. (2021). “*Terminology and classification for the fuels towards sustainability.*” (Accepted for publication) In Frontiers

In a study on the Swiss energy system, the role of storage technologies in low emission energy systems has been presented and published in a peer-reviewed conference proceedings publication:

Limpens, G., Moret, S., Guidati, G., Li, X., Maréchal, F., & Jeanmart, H. (2019). “*The role of storage in the Swiss energy transition.*” In proceedings of ECOS 2019 conference (Vol. 22, pp. 23).

Before developing the EnergyScope tools, a first model has been developed to minimise the energy invested of an electricity system. The model has been presented in a peer-reviewed journal publication:

Limpens, G., & Jeanmart, H. (2018). “*Electricity storage needs for the energy transition: An EROI based analysis illustrated by the case of Belgium.*” In Energy (Vol. 152, p. 960-973). URL: <https://doi.org/10.1016/j.energy.2018.03.180>

An extension of this study has been proposed in a peer-reviewed conference proceedings publication:

Limpens, G., & Jeanmart, H. (2018). “*Quantification of electricity storage needs for Belgium energy transition: A sensitivity analysis based on EROI.*” In proceedings of ECOS 2018 conference (Vol. 31, pp. 5-8).

Introduction

Overview

- Role of energy in our society and contribution to climate change.
- Political agreements to prevent anthropogenic GHG emissions.
- A change of paradigm: from storable to intermittent energies.
- Contributions and novelty.
- Thesis structure overview.

If someone is asked: '*what is energy?*', he will probably think first about the electricity and gas bills. Perhaps, by thinking more carefully, he will include gasoline for refilling the car. When the same person is asked: '*What is the importance of energy?*', he will probably think that it is not his main concern as it represents less than 10% of his revenues [1], and concluded that a change in the energy price won't have a significant impact on the lifestyle.

However, from a physical point of view, energy plays a crucial role that is not reflected by its gross domestic product (GDP) share but by its involvement in all activities. As a comparison, can we say that removing the brain of a body, which represents 5% of its mass, will reduce by 5% the value of the body? People have their own perception of energy. However energy remains a physical quantity that can be defined as the ability to '*change*' things. Thus, each time something *changes*, energy is involved. And energy is involved everywhere; when there is a change of temperature (heating a home), a change of material state (melting butter), a change of speed (driving a car), a change of chemical composition (the combustion of a fuel), a change of an object shape (crashing a can), etc... To summarise, energy quantifies the amount of change.

The human body consumes energy to cause change, such as walking or warming the body. It uses food (biomass) as a source of energy. Thanks to machine, humans have been able to use other types of energy carriers such as gasoline, coal or natural gas. It allowed us to increase drastically the amount of change we consume. Since the industrial revolution, more and more machines are employed to extract-grind-transform natural resources (e.g. rare earths), to move people and goods (e.g. cars, planes), to heat up environments (e.g. houses), etc. Nowadays in modern societies, they

Introduction

are leading - by far - the ability to cause change. As an illustration in 2015 in Belgium, machines were consuming 64 times more energy than Belgian people use to feed themselves¹.

Resources are needed to feed those machines. In 2015, this energy was mostly provided by the combustion of fossil fuels, which accounted for 79.7% of the world primary energy supply [3], or 77.5% in the case of Belgium [2]. Combustion of such fuels is the primary source of anthropogenic greenhouse gas (GHG) emissions [4], and thus of climate change. The Intergovernmental Panel on Climate Change (IPCC) estimated the potential impacts and associated risks of a global average temperature increase of 1.5-2°C compared to pre-industrial times. In their work [5] they predict with medium to high confidence a series of natural disasters that jeopardise billions of human beings. With an averaged temperature increase of +0.07°C per decade since 1880 and over twice that rate (+0.18°C) since 1981, the cap of 1°C is almost reached [6]. Without an inflexion in today's emission trends, the temperature increase is estimated at around 6°C, in 2100 [7]. Therefore, there is an urgent need to reduce the GHG emissions in order to avoid the latter scenario and its consequences.

How to mitigate climate change

Kaya, Yokobori, et al. [8] proposed a simple identity - which is in fact a tautology - to identify the available levers for reducing anthropogenic GHG emissions. The latter (*GHG*) is equal to the multiplication of four terms:

- *POP*: the world's population;
- $\frac{GDP}{POP}$: the gross domestic product (GDP) per capita ;
- $\frac{E}{GDP}$: the energy intensity of the GDP;
- $\frac{GHG}{E}$: the intensity of GHG emissions related to the energy.

This identity is represented hereafter:

$$GHG = POP \times \frac{GDP}{POP} \times \frac{E}{GDP} \times \frac{GHG}{E}$$

The left term, GHG emissions, must be reduced. Consequently, the product of the right terms must be reduced. Each term can be seen as a means of reducing emissions... Or, on the contrary, a reason why emissions will continue to increase. The two first terms of the identity are expected to increase. Indeed, the world's population continues to grow and could - according the United Nations - double between 2020 and 2100 [9]. For decades, the GDP per capita is continuously growing around the world [10]. And legitimately, in order to get out of poverty and insecurity, many people want to increase their standards of living. It is questionable whether developed countries could reduce their

¹In 2015, the gross inland consumption was 607.3 TWh (or 54 217 ktoe) for a population of 11.24 millions inhabitants [2]. It results in a consumption of 148 kWh per person per day. A human body consumes around 8.4 MJ per day (i.e. 2 000 kcalories), which represents 2.32 kWh of energy.

GDP, this question is out of the scope of this thesis. To compensate these rising terms, the efforts on the last two must be doubled. The third term, the energy intensity of the GDP, is limited by physical laws and can decrease until a certain threshold. In line with last decades rate, this term is foreseen to decrease at a rate of 1.5% per year [11]. In other words, the projection would result in a reduction of around 50% between 2015 and 2050.

According to the Kaya identity analysis, it results in a single option: reducing the GHG emissions intensity of the energy sector (GHG/E). These emissions are mainly related to the use of fossil energies, which are molecules based on carbon and with a high energy density. These energy carriers are burnt and it releases carbon dioxide (CO_2), a well-known anthropogenic greenhouse gas. As an example, in 2015, 95.9% of the worldwide CO_2 emissions of the energy sector were emitted by the combustion of coal (41.7%), oil (34.0%) and gas (19.2%) [3]. There are other candidates to replace these energies. Candidates that were used for a long time: wood, which has been used since the dawn of time; wind, which has made it possible to move sailing boats through oceans; geothermal energy, which was used to heat up thermal baths; hydro, which has powered water mills to grind grain; or even solar energy, which has made it possible to evaporate sea water to recover salt. These are just a few examples of the use of so-called renewable energies (REs). *Renewable* means that these energies are renewed over a short-time comparable to a human life. The last candidate that doesn't emit greenhouse gas emissions is nuclear energy, which is neither fossil, nor renewable.

In a nutshell, to mitigate climate change, an energy transition is required to reduce anthropogenic greenhouse gas emissions. The transition is often qualified as a '*decarbonisation*' of the energy system. The term carbon refers to the one included in the CO_2 molecule. Using this term is misleading as carbon, as an energy carrier, will play a key role in future energy system as its use is harmless if done in a closed cycle [12]. As an example, biomass contains a lot of carbon, thus *decarbonisation* could mean to exclude biomass. Another qualification is '*carbon-neutral*', compared to the previous term, it means that the net balance of carbon over the year should be zero, and thus fossil fuels can be used only if they are compensated by carbon capture. In a more restrictive way, the term *defossilisation* makes it possible to achieve carbon neutrality but also imposes the system to be sustainable, given that the quantities of fossil fuels are limited.

The presupposition of the impact of fossil fuels on global warming - and thus climate change - has been established since 1896 by Arrhenius [13]. Almost one century later, a consensus in the scientific community is acted in the reports of the Intergovernmental Panel on Climate Change (IPCC), in 1988 [14]. Recently, 11 258 scientists warned of a climate emergency by showing 14 trends in vital signs [15].

The role of energy policies

In the policy makers community, the first worldwide treaty to reduce GHG emissions - the 'Kyoto Protocol' - was signed in 1997 and has been ratified by 192 parties, in 2019. In 2015, the 21st United Nation Climate Change Conference negotiated the Paris Agreement, a global agreement on the reduction of GHG emissions, the text of which represented a consensus of the representatives of 196 countries. The expected key result was an agreement to set a goal of limiting global warming to 'well below 2° C' compared to pre-industrial levels (1880) [16]. Finally, in Europe, a set of policy initiatives (i.e. Green Deal) have been proposed by the European Commission with the overarching aim of making Europe climate neutral in 2050 [17].

The specific case of Belgium

Following the Earth Summit in Rio in 1992, the first Belgian governmental plan to reduce the greenhouse gas (GHG) emissions was approved in 1994 [18]. This document proposed a series of measures to reduce Belgium GHG emissions. Unfortunately, few of them were implemented [19]. Since Rio's Summit, the government and administrations has continue to work in the field² and ratified twelve legislations related to climate change, created a tool for citizens (www.my2050.be), performed four surveys (2005, 2009, 2013 and 2017), published more than 40 studies and report, etc. More recent initiatives have been taken, such as the creation of a transition fund (article 3, § 1 of the Royal Decree of 9 of May 2017) to support research, or the ratification of an interfederal energy pact³. The latest policies have been analysed by the Federal Planning Bureau (FPB) in order to ensure that they are consistent with long-term objectives. In 2017, the FPB reported that the current policies won't decrease the Belgium GHG emissions in 2050 below 70% compared to 1990 [20]. Since then, Belgium drafted a new energy and climate plan covering the period 2021-2030, this document was criticised in June 2019 by the European Commission. It recommends Belgium to take action in order to "Significantly raise the level of ambition for 2030 by at least 25 % [...], to increase the energy efficiency ambition [...], improve energy security", etc. [21]. And recently with the Green deal, the ambitions have been further increased!

The dilemma of the energy transition

However, the implementation of ambitious policies at a country scale appears as a prisoner's dilemma: on the one hand, worldwide, the collectivity has interest in limiting the impact of climate change; on the other hand, at a country level, in order to increase the country's welfare and its geopolitical power, a government has interest to continue using fossil fuels, which is cheaper than

²A federal website - www.climat.be - summarises all the measures taken by the government in relation to the climate change.

³Source: <https://www.belgium.be> and <https://www.pacte-energetique2050.be/>, consulted the 20-12-2020.

renewable options [22]. Dangelmann and Schellnhuber [23] demonstrate theoretically, and show empirically, that it is very difficult to move away from fossil fuels. Moreover, Bergh [24] explains that a drastic change in investment would create a serious risk of economic instability. Policies to mitigate climate change have technical, economical, societal, and social aspects. As a result, policy makers suffer from a difficulty to define policies as they do not know precisely the shape of future societies and how to reach the objectives.

From flexible fossil to intermittent renewables energies, a change of paradigm

Renewable energies are distributed more evenly across the globe and are sometimes cheaper than fossil fuels. Why is their use so problematic compared to fossil fuels? Since the dawn of time, humankind has used renewable energies: biomass for heating, sun for drying, or wind for grinding grain in mills. However, only one of these energies has been used extensively as shown in Figure 1: biomass. Compared to other types of renewable energy, biomass is storable. Therefore, it can be consumed when energy is needed. Some of these needs are vital, such as heat for space heating or cooking, and without biomass humankind could not have survived in some regions. On the other hand, wind, solar or hydro power are intermittent and their production is not necessarily in phase with the needs of the users. For example, it may take a few days before there is enough wind to operate a mill, and the user will compensate for this intermittence by stocking up flour.

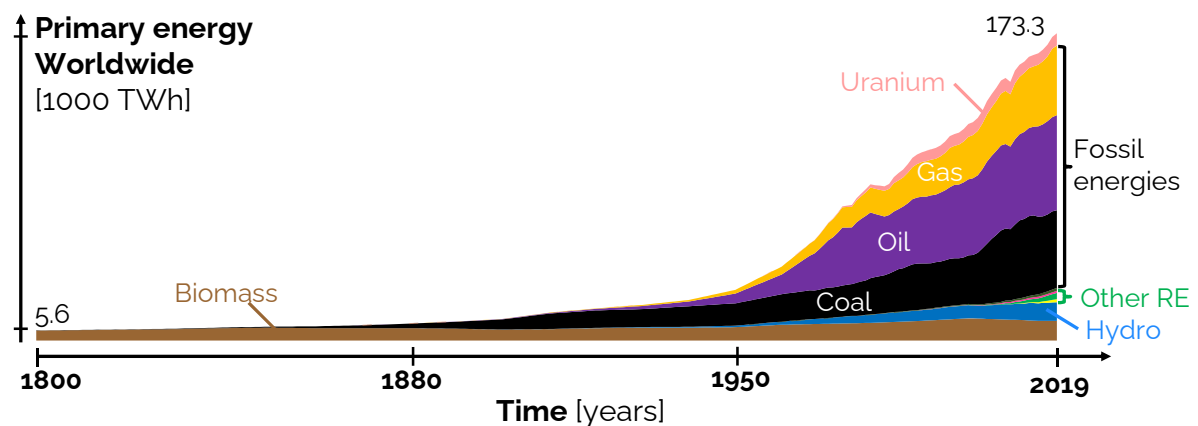


Figure 1 – Worldwide primary energy mix. Since 1800, biomass and fossil fuels (gas, oil and coal) are dominating the primary energy mix. The deployment of intermittent renewable energies (Other RE) is just starting.

Fossil fuels have been stored for millions of years, and, similarly to biomass, they can be used whenever they are needed. Their storability combined with a great versatility of application and ease of use - unlike biomass - are the reasons for the acceleration of the industrial revolution and their major contribution to the energy mix in recent centuries. Due to the rising population and energy needs, the consumptions of fossil fuels has soared and reached unsustainable levels.

The adequacy between supply and demand of fossil energies is not even mentioned, whereas supply is generally constant (i.e. the production of an oil well is not easily modulable) and on the contrary, the demand varies. This adequacy is ensured by massive storage of these fossil energies; storage that is never mentioned because it has a cost (≤ 500 €/GWh) negligible compared to its selling price (37 400 €/GWh)⁴. By way of comparison, storing heat or electricity (with batteries) cost 0.6 or 820 millions €/GWh, respectively (data presented in Appendix C).

Substituting fossil energies with intermittent renewable ones implies the loss of this nearly free storage and consequently complicates the matching of production and demand. It is this complication that penalises intermittent renewable energies: energies they produce, mainly electricity, are difficult to store. In order to ensure that production and demand are matched, energy storage will have to be rethought. This thesis investigates this storage issue, and the initial research question can be summarised as:

What is the role of energy storage technologies for the energy transition?

There are multiple storage technologies: chemical, gravitational, thermal, electro-chemical, etc. Understanding the role of storage requires to study its environment, i.e. including production and demand. Moreover, each of these technologies has its advantages. To know the ideal mix of storage technologies, they have to be put in competition. Therefore, questioning the role of storage technologies leads to the need to represent the whole energy system on a large scale.

Contribution and outlines of the thesis

Being interested in energy system modelling is akin to unlocking a Pandora's box. When opening it, one discovers a galaxy of models that answer different questions. The first step is to better understand the existing models and to start from the one that appears to be the most appropriate. The major contribution of this thesis is the improvement and extension of an open source model to represent an energy system that can include different storage technologies at different time scales (from hourly to annual). This model is then extended into a version that optimises the energy transition pathway from the existing system to a post energy transition one. Setting up a model requires a large amount of data fraught with uncertainties. A way to mitigate their impact is to perform, based on the model, a global sensitivity analysis (GSA) on the data. As illustrated in Figure 2, the combination of the different models and the GSA results in a framework for *generating energy transition pathways*. However, the proposed methodology does not include all facets of the energy transition, such as societal acceptability or the depletion of raw materials. Issues related to these

⁴Assumptions: a barrel costs roughly 1 € to store 159 liters of oil, which is equivalent to 1.7 MWh of energy. It results in a storage cost of 588 €/GWh. The brent crude oil is estimated at 60 €/barrel, which results in 37 411 €/GWh.

aspects will require a complementary study. The methodology focuses on the technical-economic dimensioning of the energy system during its transition.

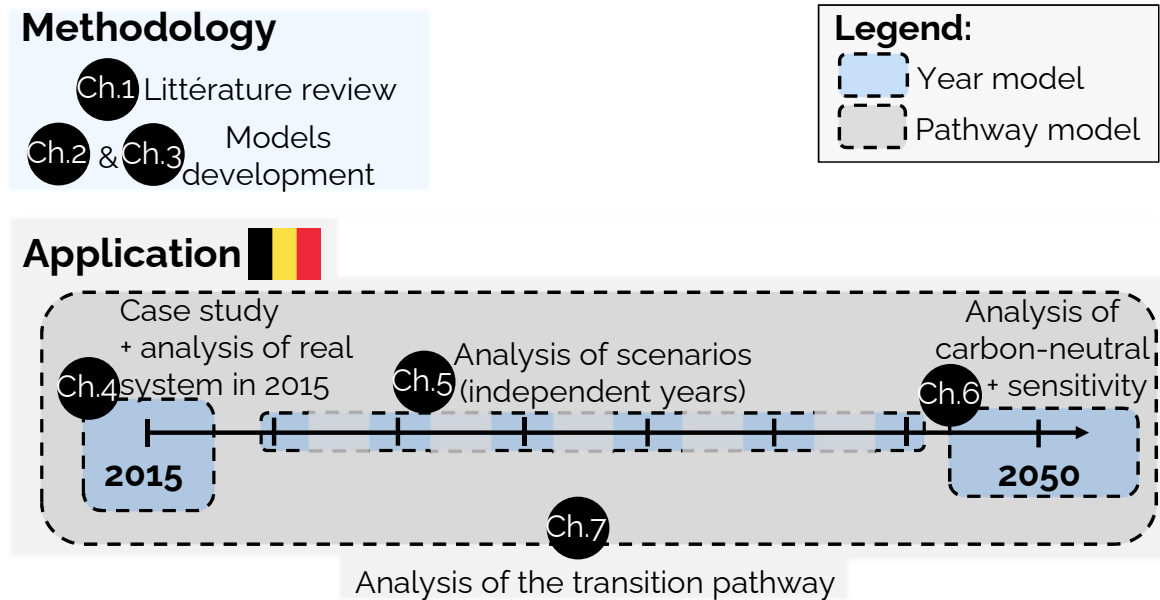


Figure 2 – Overview of the thesis structure and the arrangement of the Chapters (Ch.).

To answer to the research question, the thesis is composed of three chapters focusing on methodologies and four others on the case study and applications. The goal of each chapter and its link with others are illustrated in Figure 2. These chapters are:

- **“Energy system modelling review” (Chapter 1):** first, a classification of the different energy models is proposed. Then, once the model classes have been identified, a literature review is conducted to identify the shortcomings of the current models. Finally, a starting model as well as the necessary improvements are identified and implemented in the following chapters.
- **“Modelling for scenario analysis” (Chapter 2):** a linear programming modelling framework for scenario analysis of regional energy system is presented. Given the end-use demand, the efficiency and cost of energy conversion technologies, the availability and cost of energy resources, the model identifies the optimal investment and operation strategies to meet the demand and minimise the total annual cost or GHG emissions of the energy system in a single year. It is a simplified, yet complete, representation of an energy system, including electricity, heating and mobility; with an hourly formulation accounting for hourly to seasonal phenomena and including energy storage. The concise formulation and low computational time make it suitable for uncertainty applications, and complementary to existing (and more complex) energy models.
- **“Modelling for pathway analysis” (Chapter 3):** the model developed in Chapter 2 is improved

into a model representing the energy transition pathway from 2015 to 2050. This model optimises the investments needed throughout the different years in order to achieve carbon neutrality in 2050. As the problem is more complex, the calculation time increases and therefore this version is less relevant for uncertainty analysis.

- **“Case study: the Belgian energy system” (Chapter 4):** The selected case study must meet certain criteria. In our case, we are looking for a territory that has homogeneous weather conditions, a high energy demand and a strong dependence on fossil fuels. Belgium, among others, perfectly suits these criteria. The chapter gives an exhaustive presentation of the trends for demand, resources and technologies over the period 2015 to 2050. The data collected for the technologies will be verified by comparing their levelised cost of electricity and total cost of ownership. Finally, the consistency of the model and its data for 2015 will be verified with the real energy system in 2015.
- **“Scenarios analysis” (Chapter 5):** the scenario-model is applied to an intermediate year of the transition. A set of scenarios representing the different possibilities of the energy transition are analysed. This study allows to understand how to deploy the Belgian renewable potential, to identify the different strategies to reduce emissions in all sectors, the synergies between technologies, as well as to identify the most realistic scenarios. A more in-depth analysis on the technologies identifies the merit order between the resources and the different ways to massively integrate intermittent energies.
- **“Sensitivity analysis of the carbon-neutral energy system in 2050” (Chapter 6):** the scenario-model is then applied to understand how a carbon-neutral energy system will work. In addition, a global sensitivity analysis is used to identify the most critical uncertain parameters during the transition. These parameters are the subject of a particular attention afterwards.
- **“Energy transition pathway analysis” (Chapter 7):** the pathway-model is applied to the Belgian system from 2015 to 2050. The analysis reveals the transformation of the different sectors as well as the timing and prioritisation between them. Finally, the impact of political decisions as well as the impact of critical parameters are evaluated.

Finally, concluding remarks summarise the main findings, provide recommendations and guidance to perform a transition to a carbon-neutral energy system, and envision future perspectives.

To complement Chapters 1, 2, 4 and 6; four Appendices (A, B, C and D) provide further details for each of these chapters respectively. Appendix A elaborates the literature review by including more sources and models. Appendix B elaborates and benchmarks the clustering methods used to select typical days. Moreover, a study assesses the impact of the number of typical days on the system design and operation. Appendix C includes all the data from the reference case study for the period 2015 to 2050. These data are motivated and linked to external sources. Finally, Appendix D details the methods used to obtain the overall sensitivity analysis. The latter also includes a local analysis of the marginal cost of energy services.

1 Energy system modelling review

Chapter overview

- Classification of energy system models.
- Review of models for system planning and scenario analysis.
- Scientific contribution of the EnergyScope Typical Days (EnergyScope TD) model.

This chapter is built on a review published in Limpens et al. [25]. Since this article, the criteria to classify energy systems have been elaborated in an opinion paper Contino et al. [26].

According to Groscurth, Bruckner, and Kümmel [27], *An energy system is a system primarily designed to supply energy-services to end-users*. Thus, a human cell and the solar system can both be considered as energy systems. The energy system of interest to us is the one responsible for the current climate change: energy system that consumes the earth's fossil resources to provide energy-services to end-users: humans. These services may consist of moving humans from one place to another, or providing a warm environment or lighting our living space, etc.

There are as many models as there are questions about energy systems: how to operate a complex power plant and control its thousands of components? Which technologies can affordably substitute fossil based power plants? Both questions can be answered by using energy system models. In the first application, a suitable model must be in real time in order to give the instructions to the various components of the plants. In the second application, a suitable model must include a wide range of technologies and interactions between them. All the models have different natures for different applications.

In this thesis, the research question is: what is the role of energy storage technologies for the energy transition? To answer this question, i.e. represent properly storage technologies, there are features that the energy model should include. These features are detailed in the following paragraphs and

can be summarised in four criteria that the models will have to satisfy.

The shape of the system may drastically change from today and interactions between energy-sectors (i.e. electricity, heat and mobility) may become a key, such as making a bridge between the electricity sector and the heat and mobility ones. As proposed by Contino et al. [26]: “*Future energy systems will be smart, flexible, highly renewable, and sector-coupled. To study and plan such complex systems, whole-energy system models look at the energy system in its entirety*”. The ‘*whole*’ term is defined in opposition to the ‘*partial*’ one for the sector coverage. Indeed, most of the models cover one sector in detail and partially represent the other sectors. Thus, (i) the model must represent a ‘*whole*’ energy system and allow for the coupling of sectors.

Effective action to mitigate climate change is overdue and there is an urgent need to have consensus on energy policies. Therefore, models need to be transparent and replicable to reduce parallel efforts and allow researchers to collaborate and share their developments [28]. Thus, (ii) the model must be open source, open-data and documented. A model is deemed ‘*open source*’ if its code is available and ‘*open access*’ if a software using the code is available for free (at least partially).

There is no consensus on the energy strategy of the future system, except that intermittent renewable energies will partially replace existing flexible fossil fuel-based production units. Imposing the system design and/or simulating its operation bias the results and lead to a sub-optimal solution. Moreover, due to defossilisation, the energy system will rely heavily on intermittent resources. These have hourly to seasonal patterns, such as solar or hydraulic energy which have daily or yearly cycles, respectively. Thus, (iii) the model must optimise the design and hourly operation over a year.

Predicting the future requires many assumptions and, at best, the data used is fraught with uncertainties. These uncertainties must be included in the model in order to identify the input data that are the major source of the uncertainties in the results. Thus, (iv) the model must be adapted to numerous evaluations with a low calculation cost.

Contributions

This chapter first proposes - based on the literature - a classification of the different models. The models can be grouped into two classes, according to their main target: operation or design. Then, different sub-groups are proposed for each class according to the technical resolution and the time horizon covered. Finally, on the basis of this classification, the class and sub-groups of models necessary for this thesis will be identified.

Next, the existing models that are part of this class are reviewed. These models are then compared on the basis of the four criteria defined above which are summarised in the following questions: (i) does the model cover a whole-energy system? (ii) is the model open source/access? (iii) Does the model optimise the design and hourly operation over one year? and, (iv) what is the computing

time?

Gaps in the literature motivate the need for a new/improved model. Thus, the EnergyScope TD model and an extension are presented as novels and open sources models which bridge the gaps.

1.1 Classification of energy system models

Modelling tools for energy systems differ in terms of their temporal and spatial resolutions, level of technical details, simulation horizons, etc. In particular, two classes of models can be distinguished depending on their focus: system operation or system design (a more comprehensive review is proposed in Collins et al. [29]):

- Operational models of energy systems, which optimise the *operation* of, generally, a single sector, but do not take into account investment costs. The best example is the electricity sector. These models describe the constraints of the studied system with a high level of accuracy and have the ability to model rapid variations in renewable energy production, forecast errors or reserve markets.
- Long-term planning models, which are used to generate scenarios for the long-term evolution of an energy system. These models include investments and optimise the system *design* over multiple years. They have a lower technical resolution of the operational constraints.

In these two classes, sub-classes are defined as no model covers the whole spectrum. Figure 1.1 summarises the sub-classes in terms of *simulation horizon* and *technical resolution* (for the sake of presentation, the spatial and temporal resolutions are accounted for in the *technical resolution* dimension).

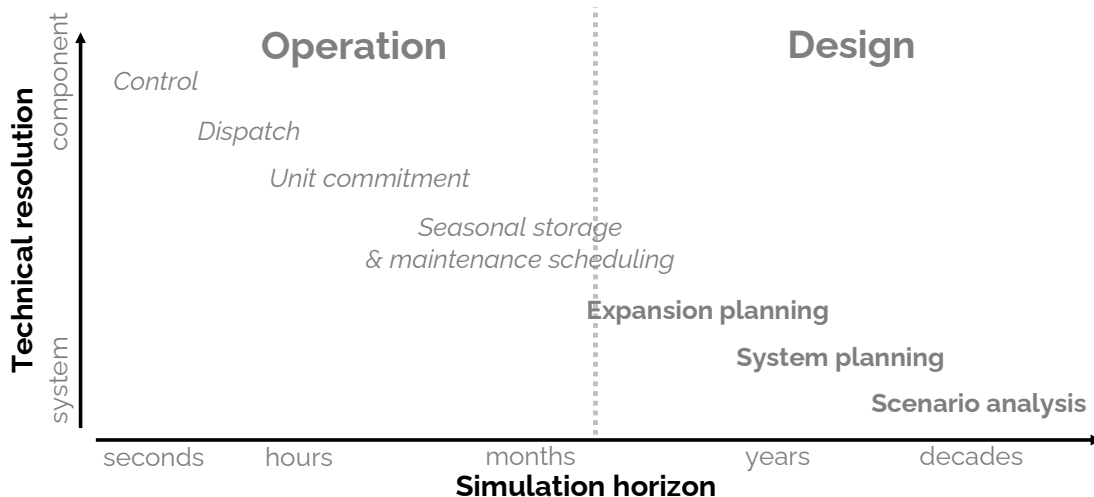


Figure 1.1 – Overview of the different scopes of models. Adapted from [30]. Scope models in bold are the one of interest in this thesis.

In the *operation* category, models can be tailored for four different applications. At any time, the energy system must be controlled (*'control models'*) which requires a very fine technical resolution of the components and take into account for the risks of failure. At a short time horizon, below the hour, the system must decide how the load is shared between the different units (*'dispatch models'*). Solving this problem involves an accurate representation of production units, such as the power ramps up, load constraints, etc. With more than 1 hour of time horizon, units can be switch-on and/or off. Thus models will decide which units must be committed (*'unit commitment models'*) to optimally dispatch the load in a near future (hours - days). Solving these problems, a coarser representation of the models is sufficient, such as simplifying the power ramp up as a start-up cost. At a month horizon, maintenance and seasonal storage levels are planned to ensure a reliable mix that could supply the load (*'seasonal storage & maintenance scheduling'*).

Having a time horizon longer than a year allows to not stick to the operation oriented models but to move to energy planning strategy, which is the scope of the *design* models. With a year horizon, new units can be built in existing sites or former units can be retrofitted and modernised (*'expansion planning'*). With a longer horizon, the overall system can be modified (*'system planning'*). When the horizon is long enough to neglect the existing system, the models can then optimise the future design of the energy system from scratch (*'Scenario analysis'*) and assess the impact of different long-term policies on the design of the system.

While *operation* models are tailored to answer questions about operation adequacy, *design* models are suited for scenario analysis and determine which is the most suitable scenario under long term objectives, such as reaching a low carbon society. This work focuses on *design* models and more specifically on long term ones: *'system planning'* and *'scenario analysis'*. A review of the models used for system planning and scenario analysis is proposed in Section 1.2 and Section 1.3, respectively.

1.2 Review of energy models for scenario analysis

In the literature, a large variety of models exists (483 in a recent review [31]). In this context, why is another energy model needed? Building on previous works by Connolly et al. [32], Pfenninger et al. [33], Prina et al. [34], Moret, Bierlaire, and Maréchal [35] and by the Open Energy Modelling Initiative (Openmod) community [36], an extensive review of 54 existing energy models and tools is performed. In this work, models of interest are summarised in Table 1.1. An exhaustive analysis is available in Appendix A.

1.2.1 Overview of existing energy models

Traditionally, energy models focus only on a given sector without considering cross-sectoral interactions. Examples of these models are EMMA [37] or SciGRID [38] which, like many others (18 out of the 54 reviewed models), model the electric power system only. However, a trend drives these models to partially integrate other sectors. As an example, Dispa-SET [39] was at first focusing on the electricity sector only and in its later versions, it partially includes sector coupling with heat (cogeneration of heat and power and heat pump (HP)) and electrical mobility. Out of the remaining 36 models, 16 partially account for the heating and the electricity sectors, and 16 partially account for the mobility sector. A major part of these models (26) consider cross-sectoral interactions in a simplified way and/or represent just a part of the energy system. Moreover, out of the 54 models, 14 are not fully open access, such as STREAM [40, 41], NEMS [42] or MARKAL/TIMES¹ [41], and 20 are not open source, such as Plexos Open EU [43] or EnergyPLAN [44].

Energy models can either optimise or simulate the investment and/or the operation of the energy system. According to Wurbs [45], a simulation model is “*a representation of a system used to predict the behaviour of the system under a given set of conditions*”, whereas an optimisation model is “*a mathematical formulation in which a formal algorithm is used to compute a set of decision-variable values that minimize or maximize an objective function subject to constraints*”. As a consequence, in a simulation the degrees of freedom are fixed *a priori* by the modeller, who defines a set of conditions which directly influence the results. Optimisation, instead, can reveal optimal configurations over a large number of available options and degrees of freedom, making it more suitable for analysing complex systems, where many alternatives need to be explored. As a drawback, optimisation is computationally more expensive, which represents a fundamental barrier for uncertainty applications [46]. In summary, optimisation and simulation are both powerful tools suitable for different applications. In this work, optimisation is adopted as a large number of variable are accounted and the optimal solution is unknown. As an example, the optimal strategy to integrate massively intermittent renewables is not known *a priori*. This approach is similar to 16 of the 54 models reviewed, which optimise - at least partially - investments and operation.

1.2.2 Comparison of energy models

In Table 1.1, we report a subset of the 54 reviewed models (from Appendix A) which present the following features: freely available; with a monthly to hourly time resolution; and modelling, at least partially, mobility and heat supply besides the electricity sector. The MARKAL/TIMES [41] model is added as the reference model. The models are compared based on the following four criteria (also used in other reviews [32–34, 36]): (i) Does the model include electricity, heating and

¹The basic TIMES version is open source and documented here : https://github.com/etsap-TIMES/TIMES_model. However, the usage of the model requires non open source tools, such as a data processing platform and GAMS model; and the users do not share their specific models, as it has been experienced for the Belgian case.

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mobility, considering cross-sectoral interactions? (ii) Is the model open source? (iii) Does it optimise the investment and/or the hourly operation strategy? (iv) Is the computational time acceptable for uncertainty analysis? An energy model answering the four criteria can be used to assess the promising technologies and synergies among all sectors in future energy systems with high shares of renewable energy (RE). Obviously, other criteria could have been applied to energy models, such as the market equilibrium or spatial resolution criteria used in other reviews [32, 33]. The simplification to four criteria is a decision of the modeler which will be later motivated in the research approach (see Chapter 2).

Table 1.1 – Comparison of existing models for large-scale system design. Legend : ✓ criterion satisfied; ✓ criterion partially satisfied; ✗ criterion not satisfied. Data from [32–34, 36, 46].

Model	Multi-sector	Optimisation	open source	Comp. time
Calliope [36, 47, 48]	✓ ^a	✓	✓	mins ^b
COMPOSE [32, 49]	✓	✓	✗	- ^c
DESSTinEE [36, 50, 51]	✓	✗	✓	s
DIETER [36, 52]	✗ ^d	✓	✓	mins ^b
EnergyPLAN [32, 44]	✓	Operation only	✗	s
EnergyScope monthly[46, 53]	✓	✓ ^e	✓	s
MARKAL/TIMES [41, 46]	✓	Investment only	✗	5-35 mins
Oemof [36, 54, 55]	✓ ^a	✓	✓	mins ^b
OSeMOSYS [36, 56, 57]	✓	✓ ^e	✓	mins
PyPSA [36, 58, 59]	✓ ^a	✓	✓	mins
STREAM [32, 40]	✓ ^f	✗	✗	- ^c
Switch [36, 60, 61]	✗ ^d	✓	✓	10-60 mins
URBS [36, 62, 63]	✗ ^d	✓	✓	20 mins

^aThe model focuses on the power system with the possibility to implement other sectors.

^bNot suitable for uncertainty characterisation, yet [36] .

^cData missing

^dEnergy system includes partially heat and transport sectors.

^eOperation is usually not resolved on a hourly base. For EnergyScope monthly, the operation are resolved over the twelve months.

^fEnergy system includes partially transport sector.

The analysis reveals that models are neither open source nor optimization-based except the following 8 models: DIETER [52], URBS [62, 63], Switch [60, 61], PyPSA [58, 59], OSeMOSYS [56, 57], Oemof [54, 55], Calliope [47, 48] and EnergyScope monthly [46, 53]. The first four models do not fully represent the energy sector as they focus mainly on the power system. DIETER offers a detailed representation of the electricity system; however, the heating sector is modelled in an excessively simplified way. URBS is a linear programming (LP) optimisation model for capacity expansion planning and unit commitment for distributed energy systems. The Mobility sector is simplified and accounts only for interactions between the power grid and electric vehicles (EVs). Switch is a capacity-planning model for power systems with large shares of RE, storage and/or demand response. Similarly to

URBS, it accounts only for EVs in the mobility sector. PyPSA is “*a free software toolbox for simulating and optimising modern electrical power systems over multiple periods*” [58]: the power system is modelled in detail, while the other sectors can be included but usually are simplified. As an example, Brown et al. [64] studied a low carbon European energy system where the heat sector does not account for industrial needs or the mobility sector is simplified to two technologies: electric vehicle and hydrogen vehicles. OSeMOSYS optimises the investment strategy over multiple years, while computing partially the operation costs based on time slices. This model is suitable to study the long-run integration of technologies and energy planning; as a drawback, it simplifies the system operations to a few critical hours over the year. As an example, the proposed application in [56] uses 6 time slices which is far from the 8760 hours of the year. Oemof “*forms a toolbox to construct comprehensive energy system models*” [54]. Its active community makes it a promising toolbox for energy system modelling. However, it is not yet ready for uncertainty modelling [36]. Similarly to Oemof, Calliope [47] is rather a toolbox than an energy model. At the time of writing, no publication using Oemof [55] and Calliope [48] adopts these toolboxes to define a multi-sector energy model representing an entire energy system including electricity, heat and mobility. The EnergyScope monthly model [46] fulfil all the criteria except the hourly resolution. This version of EnergyScope, developed for the Swiss case, resolves the operation over the twelve months. This implementation is relevant when analysing a country with little penetration of both intermittent renewables and short term storage technologies.

As shown in Table 1.1, the different models proposed in the literature have multiple specific advantages but feature one or more limitations. By consequence, none of them answers all the four criteria. These limitations impede the direct application of existing modeling frameworks in the context of this thesis. And, it motivates the need to improve an existing one.

1.3 Review of energy models for system planning

The models presented in the previous section are suitable to analyse different scenarios for a long-term goal (“*scenario analysis*”). For planning the system transition (“*system planning*”), the model of interest should have an additional feature: to represent the energy transition from the existing energy system to the long-term goal. In other words, the energy system should optimise the investment decision from today, towards a carbon neutral energy system in 2050. In addition, the model must verify that the system can be operated in the intermediary years. The required model is much larger and may require a longer calculation time. Thus, the calculation time is less constraining and can be as long as a couple of hours.

There are two methods to use models for system planning. First, the model can evaluate the overall evolution of an energy system up to the target year. Second, the model can represent a single year and being coupled with another algorithm. In this second case, the algorithm optimises the energy

transition pathway, while the model verifies the feasibility in some target years. Model for the first method is later called '*pathway*', as it represents the energy transition pathway from today system to a low carbon one. According to the classification proposed by Gironès et al. [65], the qualifier '*snapshot*' can be used in opposition to '*pathway*'. *Snapshot* models represent the energy system in a target future year, without considering existing system.

In their work, Prina et al. [34] reviewed the '*most established*' models. They sifted through different models according to the following criteria: (i) time horizon, (ii) time-step, (iii) covered energy sectors, (iv) objective function, and (v) computational time. The *pathway* models reviewed were facing at least one of the following feature: poor time discretization; only electricity sector; or/and heavy computational burden. As a consequence, Prina et al. followed the second method, and they coupled an optimisation algorithm to a *snapshot* model with a low computational time. On the basis of their analysis, the most appropriate model was EnergyPLAN. In the timeframe set for the transition, they used a multi-objective evolutionary algorithm (MOEA) which optimises the objective function based on three variables: the installed capacity of batteries, photovoltaic (PV) and onshore wind turbines.

However, this method does not meet with two of the four criteria listed in the previous section: it does not optimise *all* the design and the hourly operation over a year; and it is not open source. Indeed, the multi-objective evolutionary algorithm (MOEA) optimises three technologies and the EnergyPLAN model is a simulation tool open access only. Consequently, none of the approach proposed meets all the criteria.

1.4 Scientific contribution

Consequently, we propose a novel linear programming (LP) energy system modelling framework. The model, called EnergyScope Typical Days (EnergyScope TD), builds on - and represents a major advancement compared to - a previous version developed by Moret, Codina Gironès, Maréchal and coauthors [46, 53, 65–68]. Compare to the monthly version, the typical days version optimises the hourly operation. To keep a short computational time, the model relies on different methodology described in the following chapter.

Based on the reviewed literature for scenario analysis, the contribution of EnergyScope TD is to propose an open source model - it can be downloaded directly [69] - to optimise the design and operation of an urban or regional energy system accounting for all the energy carriers and demand with an hourly resolution over a target year. The aim of the tool is to study sector interactions and promising technologies implementation, such as short and long-term storage, for the energy transition. With respect to the listed limitations, (i) the model represents with the same level of detail the heating, mobility and electricity sectors. (ii) EnergyScope TD is open source, see repository. The

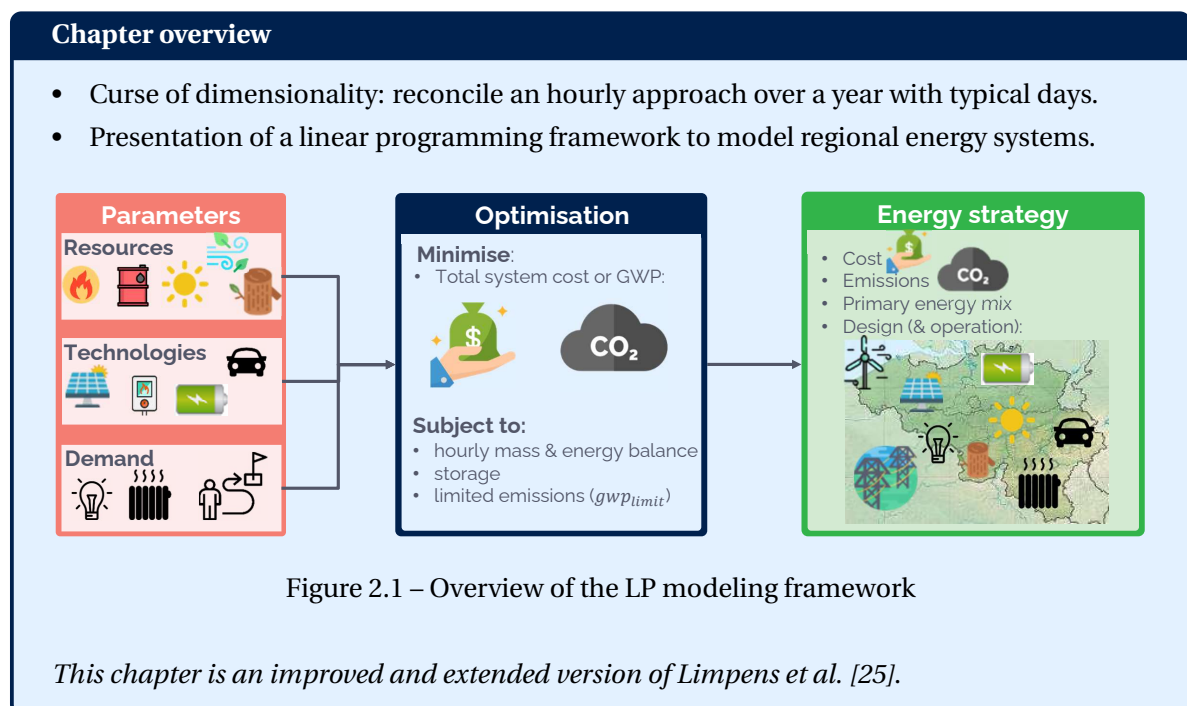
code can be run out-of-the-box, using the data for the Belgium energy system as an example. We provide a full documentation, both in terms of formulation and data input, and a user guide. (iii) The model has an hourly resolution, which allows accounting for seasonality and energy storage. (iv) Resolving a complex energy system over the 8760 hours of the year is computationally not affordable for uncertainty applications. Different approaches modelling the temporal dimension have been analysed in [70], where it is shown that resorting to well chosen typical days can be a suitable approach. EnergyScope TD uses such approach, which allows the integration of intermittent renewables as well as daily to seasonal storage options, while featuring a computational time of around 1 minute on a personal laptop, which is appropriate for uncertainty applications. The EnergyScope TD is a *snapshot* model suitable for scenario analysis, its methodology will be presented in Chapter 2.

For system planning, the EnergyScope TD short computational time and concise mathematical formulation makes it an ideal candidate to be upgraded. It results in an extension of the model, called *EnergyScope Pathway* and available at [71]. With respect to the four criteria mentioned before, the *Pathway* version keeps the same characteristics than the EnergyScope TD version for the first three ones. Indeed, the pathway version is open source and optimises the investment decisions and hourly operation of a whole-energy system for the transition period between 2015 and 2050. As a major drawback, the computational time increase significantly (hours), and thus, the *pathway* model is not suitable for numerous evaluations. However, as an additional feature, the EnergyScope pathway version is a *pathway* model suitable for system planning, its methodology will be presented in Chapter 3.

2 Modelling for scenario analysis

All models are wrong, but some are useful.

George P. Box



In its previous version - EnergyScope monthly - the model has been used in different research projects. It was first developed as an online calculator (<http://www.energyscope.ch>) to disseminate energy literacy [65] and then extended to an optimization model to support decision-makers [53]. The model has been used to analyse the integration of deep geothermal and woody biomass conversion pathways in urban systems [72]. At a national scale, it was used to assess the optimal

use of biomass [73] and its role to reduce GHG emissions [74]. In a broader context, the tool has been applied to optimise the integration of renewable energy [68], and for strategic energy planning under uncertainty [46, 53, 75].

The new version of the model aims at answering similar questions. It has been developed under a joint collaboration between EPFL and UCLouvain. The major developments are the hourly resolution, transforming the integer variables into continuous ones (i.e. from MILP to LP), and improving the energy system representation, such as by implementing storage technologies or adding the investment cost of the vehicles.

Contributions

The conceptual structure of the model is illustrated in Figure 2.1: given the end-use energy demand, the efficiency and cost of energy conversion technologies, the availability and cost of energy resources, the model identifies the optimal investment and hourly operation strategies to meet the demand and minimize the total annual cost or greenhouse gas emissions of the energy system. It is a simplified, yet complete, representation of an energy system, including electricity, heating and mobility, with a formulation based on typical days accounting for hourly dispatch, seasonality and energy storage. The concise formulation and low computational cost make it suitable for uncertainty applications, and complementary to existing and more complex energy models.

Research approach

Energy models can be developed in different ways and key modelling choices must be made between different criteria, such as the ones previously mentioned. To better understand a model, it is profitable to see the choices made by the modellers.

In terms of approach, we choose an energy-based modelling approach over a market equilibrium one (such as MARKAL/TIMES [41] or NEMS [42]), as various retrospective studies (see Moret et al. [67] for a review) show the difficulty of forecasting the evolution of markets over long planning horizons. As for the implementation, we choose optimisation over simulation as the complexity of energy systems implies a large number of available options, which - as discussed in the previous chapter (see Chapter 1) - can be better explored by optimisation. In particular, we adopt an LP formulation which offers many practical - including computational - advantages. Similarly, in terms of level of detail, our aim is a good trade-off between model granularity and computational time. With respect to this, we choose to model the entire energy system in a target future year with an hourly level of detail, resorting to typical day to ensure computational efficiency. Data uncertainty is not directly taken into account in the model and therefore a perfect foresight is assumed for each evaluation of the model. However, in order to evaluate the impact of these uncertainties, a global sensitivity analysis method will be presented and applied in Chapter 6. This method requires many

evaluations of the model, and that motivates a need for a short computational time.

Overall, these choices are appropriate for a *whole* energy system model that can answer scenario analysis questions such as *how to deal with the intermittency of RE?* or *what will be the role of storage technologies in the energy transition?*

As a consequence of these choices, we have developed a methodology in two steps, as shown in Figure 2.2. Based on the input data (resources, technologies and demand):

- the first step consists in pre-processing the time series and solving a mixed-integer linear programming (MILP) problem to determine the adequate set of typical days (Section 2.1).
- the second step is the main energy model: it identifies the optimal design and operation of the energy system over the selected typical days (Section 2.2), i.e. technology selection, sizing and operation for a target future year.

These two steps can be computed independently. Usually, the first step is computed once for an energy system with given weather data whereas the second step is computed several times (once for each different scenario).

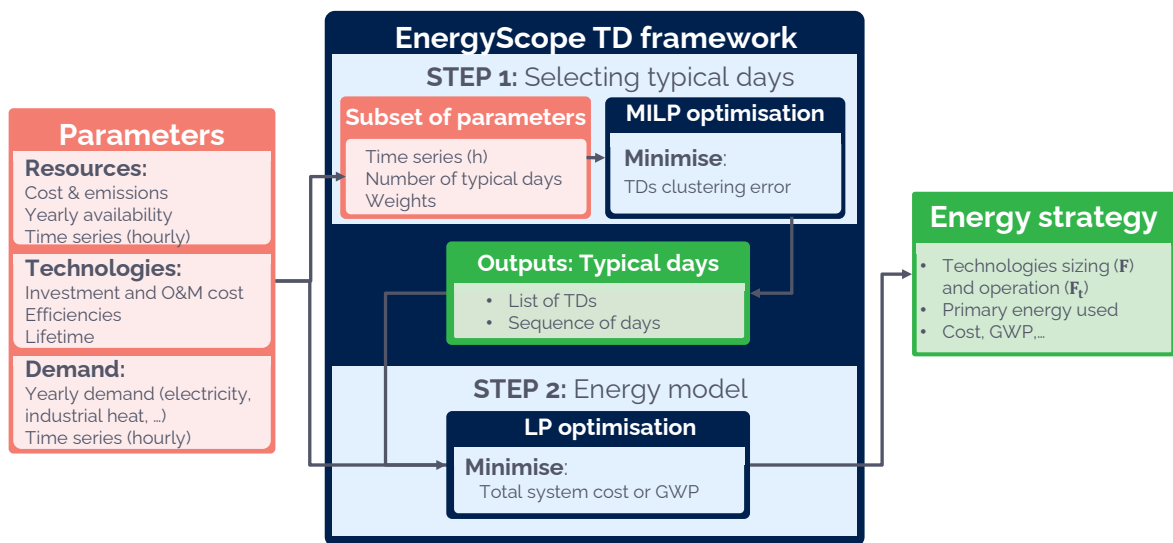


Figure 2.2 – Overview of the EnergyScope TD framework in two-steps. **STEP 1:** optimal selection of typical days. **STEP 2:** Energy system model (Section 2.2). The first step processes only a subset of parameters, which account for the 8760h time series. Abbreviations: typical day (TD), mixed-integer linear programming (MILP), linear programming (LP) and global warming potential (GWP)

2.1 Curse of dimensionality: selection of typical days

Due to computational restrictions, energy system models rarely optimise the 8760h of the year. As an example, running our model with 8760h time series takes more than 19 hours; while the

hereafter presented methodology needs approximately 1 minute. A typical solution is to use a subset of representative days called typical day (TD); this is a trade-off between introducing an approximation error in the representation of the energy system (especially for short-term dynamics) and computational time. Resorting to TDs has the main advantage of reducing the computational time by several orders of magnitude. Usually, studies use between 6 and 20 TDs [76–79], sometimes even less [80, 81]. Hereafter (Section 2.1.1), different clustering methods will be presented.

2.1.1 Selecting Typical Days

In the literature, various approaches exist to select TDs. The easiest approaches are based on heuristic algorithms, such as selecting 2 extreme days per season, i.e. if based on demand, the ones with the highest and the lowest demand [80]. More advanced approaches exist, selecting TDs by clustering days which are similar based on given criteria. In this work, the criterion is to cluster days with similar demand and weather data. Hence, we consider five time series to define our clusters: two for end-use demand (electricity and space heating) and three for weather conditions (solar irradiance, onshore wind speed and offshore wind speed). Depending on the importance given to each time series, weights are associated to them. For every resulting cluster, the most representative existing day, also called centroid, can be taken as the TD of the cluster.

In a previous work [25], We compared four algorithms for TDs selection: a commonly used one and three recently developed algorithms. The first and reference method is the k-medoids [82, 83], a common and computationally efficient method [84] applied in similar studies [76, 81]. For every possible combination of TDs, the method clusters days by minimising their Euclidean distance. The second method is a revisited version of the k-medoids algorithm developed by Domínguez-Muñoz et al. [81]. It is an integer formulation of the k-medoids problem based on an alternative method proposed by Vinod [85]: a MILP problem clusters days by minimising the distance between their time series and the optimal cluster time series. The third and fourth - here referred to as ‘*Poncelet*’ and ‘*Poncelet HYB*’, respectively - are both proposed by Poncelet et al. [80]. For both methods, the criterion is based on *duration curves*¹. A MILP problem is solved to minimise the error between the real duration curve and the approximated duration curve based on TDs. Similarly to the k-medoids method, Poncelet’s method tries every combination of TDs, which is again highly combinatorial. Hence, a variant called ‘*Poncelet-HYB*’ is proposed, which resorts on samples of TDs.

Each method has its advantages depending on the applications. In [25], we compared the performance of each method to the specific case of EnergyScope TD. The comparison is detailed in Appendix B and key findings are summarised in Table 2.1. The k-medoids variant developed by Domínguez-Muñoz et al. [81] appeared to be the most efficient with an affordable computational

¹For a given hourly time series, the duration curve is a graph representing the time series sorted from the highest value (on the left) to the lowest (on the right): as an example; for the power duration curve, on a x - y graph, the peak yearly power demand hour is at $x = 1$, the lowest demand hour is at $x = 8760$.

Table 2.1 – Performance of clustering methods to compute 12 typical days. Calculation of clustering methods are detailed in Appendix B and numerical values are simplified with a representation with ++, +, – and – –.

Criteria	k-medoids	Domínguez-Muñoz	Poncelet	Poncelet HYB
Computational cost [s]	3750	876	3600	3253
Clustering error	- -	++	+	+
Duration curve error	-	++	+	+

time. This method is used in the following to identify the TDs.

2.1.2 Implementing seasonality with typical days

Using TDs can introduce some limitations. As an example, traditionally, model based on TDs are not able to include inter-days or seasonal storage due to the discontinuity between the selected days. Thus, they assess only the capacity of production without accounting for storage capacities. Carbon-neutral energy system will require long term storage and thus, this limitation must be overcome. Therefore, we implemented a method proposed by Gabrielli et al. [76] to rebuild a year based on the typical days by defining a sequence of typical days. This allows to optimise the storage level of charge over the 8760h of the year. Gabrielli et al. [76] assigned a TD to each day of the year; all decision variables are optimised over the TDs, apart from the amount of energy stored, which is optimised over 8760h.

From their work [76], we have implemented the “*Coupling typical days*” method (also called “*Method 1*” in [76]). Each day of the year is related to its TD through a sequence (TD_OF_DAY). With this approach, each day of the year is described by a given TD, and the energy stored during the last hour of every day is connected to the energy stored at the first hour of the following day.

Figure 2.3 gives an illustration of how the storage works over a week with 3 TDs. In this example, the storage is used during weekdays and more especially cloudy ones (Monday, Thursday and Friday); during the weekend, instead, the storage is refilled. The power is resolved considering independent TDs. On the contrary, the energy is resolved considering the 8760h of the year.

The use of a limited number of typical days, even with a reconstruction method, leads to a bias in yearly demand and capacity factors. These biases are corrected by normalising the time series implemented in STEP 2. For example, if, based on the sequence of typical days, the onshore wind capacity factor is 25.2%, while the historical value is 24.3%, then the associated time series will be decreased by 3.6% ($\approx 1 - 24.3\%/25.2\%$).

A comparison has been conducted between the reference solution - relying on 365 TDs - and solutions using different numbers of TDs: 4, 8, 12, 24 and 48. For each number, the model (STEP 2)

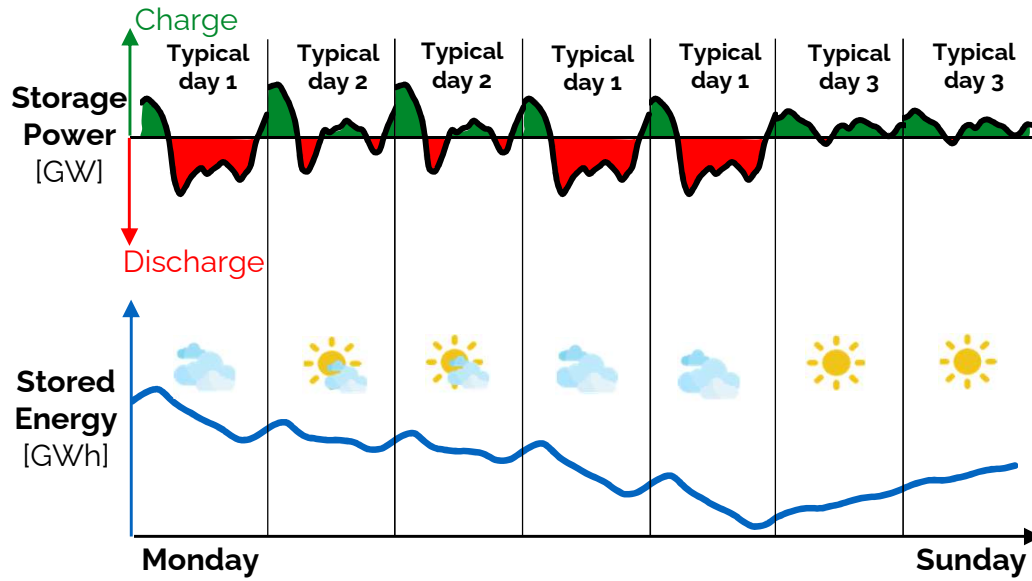


Figure 2.3 – Illustration of the typical days reconstruction method proposed by [76] over a week. The example is based on 3 TDs: TD 1 represents a cloudy weekday, applied to Monday, Thursday and Friday; TD 2 is a sunny weekday, applied to Tuesday and Wednesday; and TD 3 represents sunny weekend days. The power profile (above) depends solely on the typical day but the energy stored (below) is optimised over the 8760 hours of the year (blue curve). Note that the level of charge is not the same at the beginning (Monday 1 am) and at the end of the week (Sunday 12 pm).

Table 2.2 – Comparison of major differences when using different number of typical days. Abbreviations: computational (comp.), combined cycle gas turbine (CCGT), cogeneration of heat and power (CHP), thermal (therm.) and number (Nbr.).

Nbr. of TDs [days]	Comp. time [s]	Therm. storage [GWh]	Electricity flexibility strategy		
			CHP [%]	CCGT [%]	Import [%]
365	70 240	261	25.0	75.0	
48	296	198		100	
24	135	182		100	
12	92	101		100	
8	91	38	8.3	4.2	87.5
4	54	33		100	

was run and the outputs were compared. The evaluation of the key performance indicators (i.e. total global warming potential or cost) for different numbers of TDs gave similar values. Nevertheless, there are three major differences: (i) the computational time; (ii) the thermal storage capacities; (iii) the strategy to bring flexibility in the electricity sector. Table 2.2 summarises the results for these differences (details available in Appendix B.2). Using a limited number of TDs reduces drastically the computational time, but introduces an error in the storage sizing, mainly the ones used for weeks to seasonal storage (i.e. thermal storage in our application). With 8 TDs or less, the latter type of storage is not resolved (i.e. not installed). To ensure a short computational time and an accurate results, the best trade-off is to use 12 typical days. With this number of typical days, the computational time was as short as relying on 4 and 8 typical days. As a counterpart, the long-term thermal storage, was downsized by a factor of 2. The change in electricity flexibility strategy is not correlated to the number of TDs used but reflects a typical characteristic of linear programming (LP) problems: the three different strategies have a similar total annual system cost. Thus, a little change in the problem can drive to a big change in the design and operation. This intrinsic behavior of LP motivates the consideration of uncertainties.

2.2 Energy system model

Hereafter, we present the core of the energy model. First, we introduce the conceptual modelling framework with an illustrative example, in order to clarify as well the nomenclature. Second, we introduce the constraints of the energy model (case study and data will be detailed in a following Chapter 4).

2.2.1 Linear programming formulation

The model is mathematically formulated as a linear programming (LP) problem [86]. Figure 2.4 represents - in a simple manner - what is a LP problem and the nomenclature used. In italic capital letters, *SETS* are collections of distinct items (as in the mathematical definition), e.g. the *RESOURCES* set regroups all the available resources (NG, WOOD, etc.). In italic lowercase letters, *parameters* are known values (inputs) of the model, such as the demand or the resource availability. In bold with first letter in uppercase, **Variables** are unknown values of the model, such as the installed capacity of photovoltaic (PV). These values are determined (optimised) by the solver within an upper and a lower bound (both being parameters). As an example, the installed capacity of wind turbines is a decision variable; this quantity is bounded between zero and the maximum available potential. *Decision variables* can be split in two categories: independent decision variables, which can be freely fixed, and dependent decision variables, which are linked via equality constraints to the previous ones. As an example the investment cost for wind turbines is a variable but it directly depends on the number of wind turbines, which is an independent decision variable. *Constraints* are inequality

or equality restrictions that must be satisfied. The problem is subject to (s.t.) constraints that can enforce, for example, an upper limit for the availability of resources, energy or mass balance, etc. Finally, an *objective function* is a particular constraint whose value is to be maximised (or minimised).

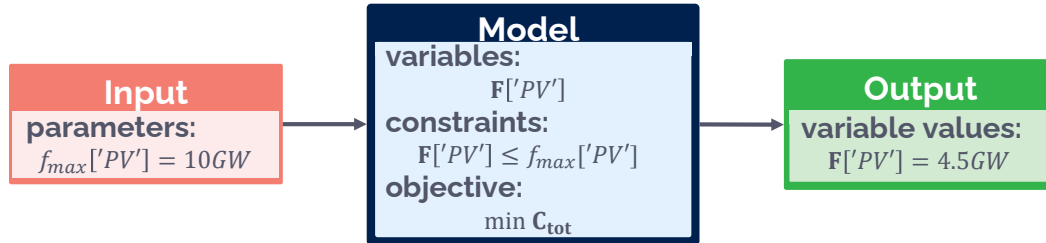


Figure 2.4 – Conceptual illustration of a linear programming problem and the nomenclature used. Symbol description: maximum installed size of a technology (f_{max}), installed capacity of a technology (F) and total system cost (C_{tot}). In this example, a specific technology (photovoltaic ('PV')) has been chosen from the set TECHNOLOGY.

2.2.2 Conceptual modelling framework

The proposed modelling framework is a simplified representation of an energy system accounting for the energy flows within its boundaries. Its primary objective is to satisfy the energy balance constraints, meaning that the demand is known and the supply has to meet it. In the energy modelling practice, the energy demand is often expressed in terms of final energy consumption (FEC). According to the definition of the European commission, FEC is defined as “*the energy which reaches the final consumer's door*” [87]. In other words, the FEC is the amount of input energy needed to satisfy the end-use demand (EUD) in energy services. As an example, in the case of decentralised heat production with a natural gas (NG) boiler, the FEC is the amount of NG consumed by the boiler; the EUD is the amount of heat produced by the boiler, i.e. the heating service needed by the final user.

The input for the proposed modelling framework is the EUD in energy services, represented as the sum of four energy-sectors: electricity, heating, mobility and non-energy demand; this replaces the classical economic-sector based representation of energy demand. Heat is divided in three end-use types (EUTs): high temperature heat for industry, low temperature for space heating and low temperature for hot water. Mobility is divided in two EUTs: passenger mobility and freight². Non-energy demand is, based on the International Energy Agency (IEA) definition, “*fuels that are used as raw materials in the different sectors and are not consumed as a fuel or transformed into another fuel.*” [88]. As examples, the European Commission includes as non-energy the following materials: “*chemical feed-stocks, lubricants and asphalt for road construction.*” [89].

²Passenger transport activity from aviation is accounted in passenger mobility (excluding international extra-European Union (EU) travels).

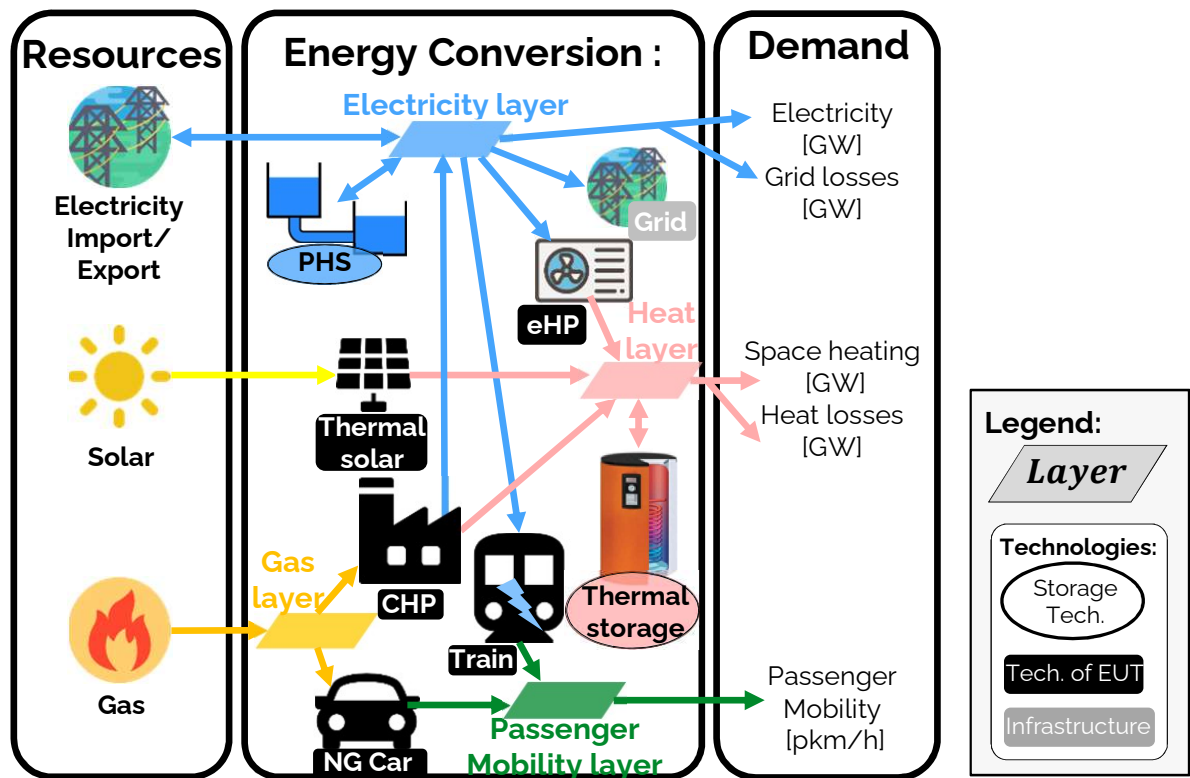


Figure 2.5 – Conceptual example of an energy system with 3 resources, 8 technologies (of which 2 storages (in colored oval) and 1 infrastructure (grey rectangle)) and 3 end use demands. Abbreviations: pumped hydro storage (PHS), electrical heat pump (eHP), cogeneration of heat and power (CHP), compressed natural gas (CNG). Some icons from [90].

A simplified conceptual example of the energy system structure is proposed in Figure 2.5. The system is split in three parts: resources, energy conversion and demand. In this illustrative example, resources are solar energy, electricity and NG. The EUD are electricity, space heating and passenger mobility. The energy system encompasses all the energy conversion technologies needed to transform resources and supply the EUD. In this example, Solar and NG resources cannot be directly used to supply heat. Thus, they use technologies, such as boilers or cogeneration of heat and power (CHP) for NG, to supply the end-use type (EUT) layer (e.g. the high temperature industrial heat layer). *Layers* are defined as all the elements in the system that need to be balanced in each time period; they include resources and EUTs. As an example, the electricity layer must be balanced at any time, meaning that the production and storage must equal the consumption and losses. These layers are connected to each other by *technologies*. We define three types of technologies: *technologies of end-use type*, *storage technologies* and *infrastructure technologies*. A technology of end-use type can convert the energy (e.g. a fuel resource) from one layer to an EUT layer, such as a CHP unit that converts NG into heat and electricity. A storage technology converts energy from a layer to the same one, such as thermal storage (TS) that stores heat to provide heat. In this example (Figure 2.5), there are two storage technologies: thermal storage for heat and pumped hydro storage (PHS) for electricity. An infrastructure technology gathers the remaining technologies, including the networks, such as the power grid and district heating networks (DHNs), but also technologies linking non end-use layers, such as methane production from wood gasification or hydrogen production from methane reforming.

As an illustrative example of the concept of *layer*, Figure 2.6 gives a perspective of the electricity layer which is the most complex one, since the electrification of other sectors is foreseen as a key of the energy transition [91]. In the proposed version, 42 technologies are related to the electricity layer. 9 technologies produce exclusively electricity, such as combined cycle gas turbine (CCGT), PV or wind. 12 cogenerations of heat and power (CHPs) produce heat and electricity, such as industrial waste CHP. 6 technologies are related to the production of synthetic fuels and carbon capture and storage (CCS). 1 infrastructure represents the grid. 4 storage technologies are implemented, such as PHS, batteries or vehicle-to-grid (V2G). The remains are consumers regrouped in the electrification of heat and mobility. Electrification of the heating sector is supported by direct electric heating but also by the more expensive but more efficient electrical heat pumps for low temperature heat demand. Electrification of mobility is achieved via electric public transportation (train, trolley, metro and electrical/hybrid buses), electric private transportation including electric vehicles and hydrogen cars³ and trains for freight.

The energy system is formulated as a linear programming (LP) problem. It optimises the design by computing the installed capacity of each technology, as well as the operation in each period, to meet the energy demand and minimize the total annual cost of the system. In the following, we present

³Hydrogen can be produced based on many feed-stocks, among them electricity used for electrolyzers.

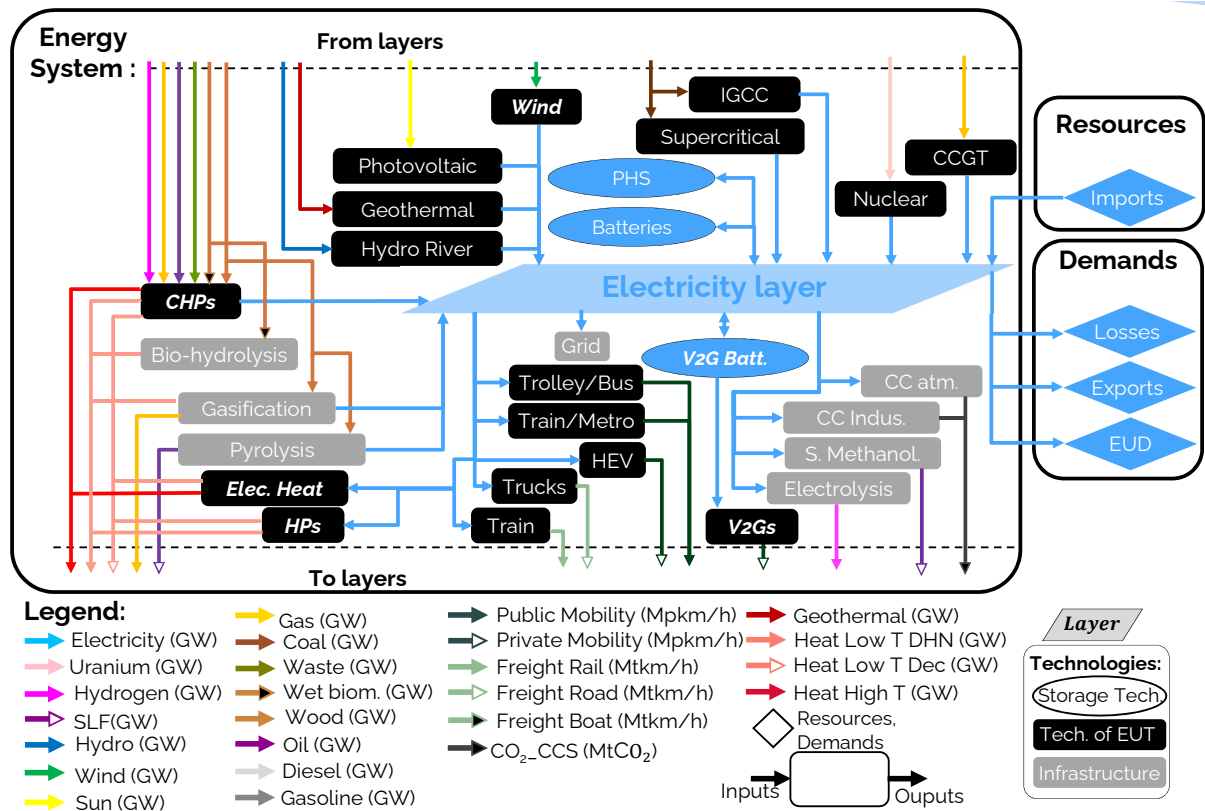


Figure 2.6 – Representation of the Electricity layer with all the technologies implemented in EnergyScope Typical Days. **Bold *Italic technologies*** represent a group of different technologies. Abbreviations: atmospheric (atm.), Carbon capture (CC), combined cycle gas turbine (CCGT), cogeneration of heat and power (CHP), heat pump (HP), electricity (elec.), heat pump (HP), industrial (ind.) integrated gasification combined cycle (IGCC), pumped hydro storage (PHS), synthetic methanolation (S. Methanol.), vehicle-to-grid (V2G), end-use demand (EUD).

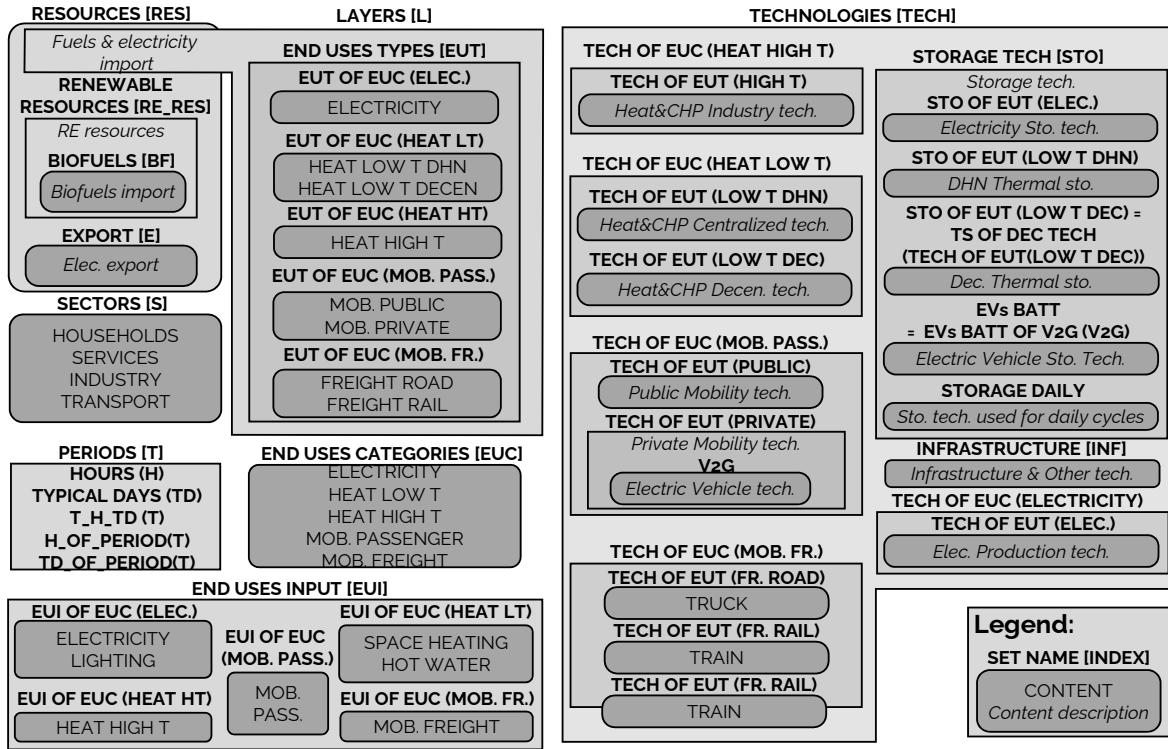


Figure 2.7 – Visual representation of the sets and indices used in the LP framework. Abbreviations: space heating (SH), hot water (HW), temperature (T), mobility (MOB), passenger (Pass.), vehicle-to-grid (V2G), thermal storage (TS).

the complete formulation of the model in two parts. First, all the terms used are summarised in a figure and tables: Figure 2.7 for sets, Tables 2.3 and 2.4 for parameters, and Tables 2.5 and 2.6 for variables. On this basis, the equations representing the constraints and the objective function are formulated in Figure 2.8 and Eqs. (2.1)-(2.37) and described in the following paragraphs.

2.2.3 Sets, parameters and variables

Figure 2.7 gives a visual representation of the sets with their relative indices used in the followings. Tables 2.3 and 2.4 list and describe the model parameters. Tables 2.5 and 2.6 list and describe the independent and dependent variables, respectively.

2.2.4 Linear Programming model formulation

In the following, the overall LP formulation is proposed through Figure 2.8 and equations (2.1)-(2.37) the constraints are regrouped in paragraphs. It starts with the calculation of the end-use demand. Then, the cost, the global warming potential (GWP) and the objective functions are introduced. Then, it follows with more specific paragraphs, such as *storage* or *vehicle-to-grid* implementations.

Table 2.3 – Time series parameters

Parameter	Units	Description
$\%_{elec}(h, td)$	[-]	Yearly time series (adding up to 1) of electricity end-uses
$\%_{sh}(h, td)$	[-]	Yearly time series (adding up to 1) of SH end-uses
$\%_{pass}(h, td)$	[-]	Yearly time series (adding up to 1) of passenger mobility end-uses
$\%_{fr}(h, td)$	[-]	Yearly time series (adding up to 1) of freight mobility end-uses
$c_{p,t}(tech, h, td)$	[-]	Hourly maximum capacity factor for each technology (default 1)

End-use demand

Imposing the end-use demand (EUD) instead of the FEC has two advantages. First, it introduces a clear distinction between demand and supply. On the one hand, the demand concerns the definition of the end-uses, i.e. the requirements in energy services (e.g. the mobility needs). On the other hand, the supply concerns the choice of the energy conversion technologies to supply these services (e.g. the types of vehicles used to satisfy the mobility needs). Based on the technology choice, the same EUD can be satisfied with different FEC, depending on the efficiency of the chosen energy conversion technology. Second, it facilitates the inclusion in the model of electric technologies for heating and transportation.

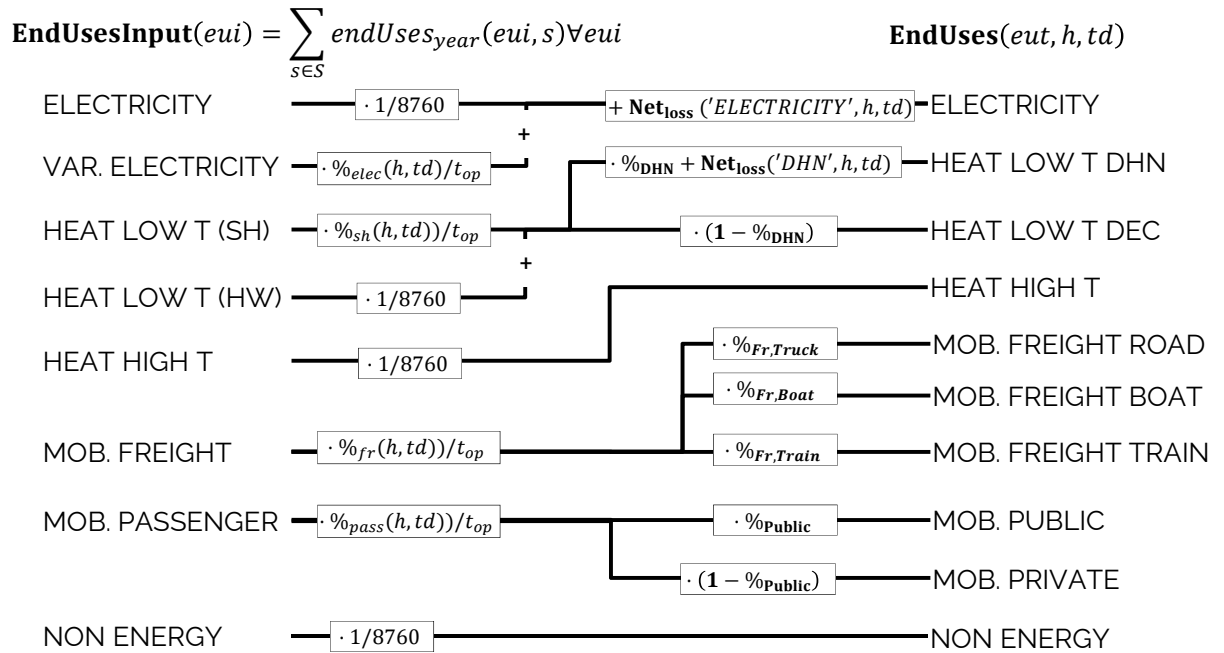


Figure 2.8 – Hourly **EndUses** demands calculation starting from yearly demand inputs (*endUsesInput*). Adapted from [46]. Abbreviations: space heating (sh), district heating network (DHN), hot water (HW), passenger (pass) and freight (fr).

The hourly end-use demands (**EndUses**) are computed based on the yearly end-use demand (*endUs-*

Table 2.4 – List of parameters (except time series).

Parameter	Units	Description
$\tau(tech)$	[-]	Investment cost annualization factor
i_{rate}	[-]	Real discount rate
$endUses_{year}(eui, s)$	[GWh/y] ^a	Annual end-uses in energy services per sector
$endUsesInput(eui)$	[GWh/y] ^a	Total annual end-uses in energy services
re_{share}	[-]	minimum share [0;1] of primary RE
gwp_{limit}	[ktCO ₂ -eq/y]	Higher CO ₂ -eq emissions limit
$\%_{public,min}, \%_{public,max}$	[-]	Lower and upper limit to $\%_{Public}$
$\%_{fr,rail,min}, \%_{fr,rail,max}$	[-]	Lower and upper limit to $\%_{Fr,Rail}$
$\%_{fr,boat,min}, \%_{fr,boat,max}$	[-]	Lower and upper limit to $\%_{Fr,Boat}$
$\%_{fr,truck,min}, \%_{fr,truck,max}$	[-]	Lower and upper limit to $\%_{Fr,Truck}$
$\%_{dhn,min}, \%_{dhn,max}$	[-]	Lower and upper limit to $\%_{Dhn}$
$t_{op}(h, td)$	[h]	Time period duration (default 1h)
$f_{min}, f_{max}(tech)$	[GW] ^{ab}	Min./max. installed size of the technology
$f_{min}, \%_{f_{max}}, \%_{f_{min}}(tech)$	[-]	Min./max. relative share of a technology in a layer
$avail(res)$	[GWh/y]	Resource yearly total availability
$c_{op}(res)$	[M€ ₂₀₁₅ /GWh]	Specific cost of resources
veh_{capa}	[km-pass/h/veh.] ^a	Mobility capacity per vehicle (veh.).
$\%_{Peak_{sh}}$	[-]	Ratio peak/max. space heating demand in typical days
$f(res \cup tech \setminus sto, l)$	[GW] ^c	Input from (< 0) or output to (> 0) layers. $f(i, j) = 1$ if j is main output layer for technology/resource i
$c_{inv}(tech)$	[M€ ₂₀₁₅ /GW] ^{cb}	Technology specific investment cost
$c_{maint}(tech)$	[M€ ₂₀₁₅ /GW/y] ^{cb}	Technology specific yearly maintenance cost
$lifetime(tech)$	[y]	Technology lifetime
$gwp_{constr}(tech)$	[ktCO ₂ -eq./GW] ^{ab}	Technology construction specific GHG emissions
$gwp_{op}(res)$	[ktCO ₂ -eq./GWh]	Specific GHG emissions of resources
$c_p(tech)$	[-]	Yearly capacity factor
$\eta_{sto,in}, \eta_{sto,out}(sto, l)$	[-]	Efficiency [0; 1] of storage input from/output to layer. Set to 0 if storage not related to layer.
$\%_{sto_{loss}}(sto)$	[1/h]	Losses in storage (self discharge)
$t_{sto_{in}}(sto)$	[-]	Time to charge storage (Energy to power ratio)
$t_{sto_{out}}(sto)$	[-]	Time to discharge storage (Energy to power ratio)
$\%_{sto_{avail}}(sto)$	[-]	Storage technology availability to charge/discharge
$\%_{net_{loss}}(eut)$	[-]	Losses coefficient [0; 1] in the networks (grid and DHN)
$ev_{batt,size}(v2g)$	[GWh]	Battery size per V2G car technology
$c_{grid,extra}$	[M€ ₂₀₁₅ /GW]	Cost to reinforce the grid per GW of intermittent renewable
$elec_{import,max}$	[GW]	Maximum net transfer capacity
$solar_{area}$	[km ²]	Available area for solar panels
$power_{density}_{pv}$	[GW/km ²]	Peak power density of PV
$power_{density}_{solar\ thermal}$	[GW/km ²]	Peak power density of solar thermal

^a[Mpkkm] (millions of passenger-km) for passenger, [Mtkm] (millions of ton-km) for freight mobility end-uses

^b[GWh] if $tech \in STO$

^c[Mpkkm/h] for passenger, [Mtkm/h] for freight mobility end-uses

Table 2.5 – Independent variables. All variables are continuous and non-negative, unless otherwise indicated.

Variable	Units	Description
$\%Public$	[-]	Ratio [0; 1] public mobility over total passenger mobility
$\%Fr,Rail$	[-]	Ratio [0; 1] rail transport over total freight transport
$\%Fr,Boat$	[-]	Ratio [0; 1] boat transport over total freight transport
$\%Fr,Truck$	[-]	Ratio [0; 1] truck transport over total freight transport
$\%Dhn$	[-]	Ratio [0; 1] centralized over total low-temperature heat
$F_t(tech)$	[GW] ^a	Installed capacity with respect to main output
$F_t(tech \cup res, h, td)$	[GW] ^a	Operation in each period
$Sto_{in}, Sto_{out}(sto, l, h, td)$	[GW]	Input to/output from storage units
$P_{Nuclear}$	[GW]	Constant load of nuclear
$\%PassMob(TECH OF EUC(PassMob))$	[-]	Constant share of passenger mobility
$\%FreightMob(TECH OF EUC(FreightMob))$	[-]	Constant share of freight mobility
$\%HeatDec(TECH OF EUT(HeatLowTDEC)\{DecSolar\})$	[-]	Constant share of low temperature heat decentralised supplied by a technology plus its associated thermal solar and storage
$F_{sol}(TECH OF EUT(HeatLowTDEC)\{DecSolar\})$	[GW]	Solar thermal installed capacity associated to a decentralised heating technology
$F_{tsol}(TECH OF EUT(HeatLowTDEC)\{DecSolar\})$	[GW]	Solar thermal operation in each period

^a[Mpk] (millions of passenger-km) for passenger, [Mtkm] (millions of ton-km) for freight mobility end-uses, [GWh] if $tech \in STO$

Table 2.6 – Dependent variable. All variables are continuous and non-negative, unless otherwise indicated.

Variable	Units	Description
$EndUses(l, h, td)$	[GW] ^a	End-uses demand. Set to 0 if $l \notin EUT$
C_{tot}	[M€ ₂₀₁₅ /y]	Total annual cost of the energy system
$C_{inv}(tech)$	[M€ ₂₀₁₅]	Technology total investment cost
$C_{maint}(tech)$	[M€ ₂₀₁₅ /y]	Technology yearly maintenance cost
$C_{op}(res)$	[M€ ₂₀₁₅ /y]	Total cost of resources
GWP_{tot}	[ktCO ₂ -eq./y]	Total yearly GHG emissions of the energy system
$GWP_{constr}(tech)$	[ktCO ₂ -eq.]	Technology construction GHG emissions
$GWP_{op}(res)$	[ktCO ₂ -eq./y]	Total GHG emissions of resources
$Net_{loss}(eut, h, td)$	[GW]	Losses in the networks (grid and DHN)
$Sto_{level}(sto, t)$	[GWh]	Energy stored over the year

^a[Mpk] (millions of passenger-km) for passenger, [Mtkm] (millions of ton-km) for freight mobility end-uses

esInput), distributed according to its time series (listed in Table 2.3). Figure 2.8 graphically presents the constraints associated to the hourly end use demand (**EndUses**), e.g. the public mobility demand at time t is equal to the hourly passenger mobility demand times the public mobility share ($\%Public$).

Electricity end-uses result from the sum of the electricity-only demand, assumed constant throughout the year, and the variable demand of electricity, distributed across the periods according to $\%_{elec}$. Low-temperature heat demand results from the sum of the yearly demand for hot water (HW), evenly shared across the year, and space heating (SH), distributed across the periods according to $\%_{sh}$. The percentage repartition between centralized (DHN) and decentralized heat demand is defined by the variable $\%_{DHN}$. High temperature process heat and mobility demand are evenly distributed across the periods. Passenger mobility demand is expressed in passenger-kilometers (pkms), freight transportation demand is in ton-kilometers (tkms). The variable $\%Public$ defines the penetration of public transportation in the passenger mobility sector. Similarly, $\%Rail$, $\%Boat$ and $\%Truck$ define the penetration of train, boat and trucks for freight mobility, respectively.

Cost, emissions and objective function

$$\min \mathbf{C}_{tot} = \sum_{j \in TECH} \left(\tau(j) \mathbf{C}_{inv}(j) + \mathbf{C}_{maint}(j) \right) + \sum_{i \in RES} \mathbf{C}_{op}(i) \quad (2.1)$$

$$\text{s.t. } \tau(j) = \frac{i_{rate}(i_{rate} + 1)^{lifetime(j)}}{(i_{rate} + 1)^{lifetime(j)} - 1} \quad \forall j \in TECH \quad (2.2)$$

$$\mathbf{C}_{inv}(j) = c_{inv}(j) \mathbf{F}(j) \quad \forall j \in TECH \quad (2.3)$$

$$\mathbf{C}_{maint}(j) = c_{maint}(j) \mathbf{F}(j) \quad \forall j \in TECH \quad (2.4)$$

$$\mathbf{C}_{op}(i) = \sum_{t \in T | \{h, td\} \in T_H_TD(t)} c_{op}(i) \mathbf{F}_t(i, h, td) t_{op}(h, td) \quad \forall i \in RES \quad (2.5)$$

The objective, Eq. (2.1), is the minimisation of the total annual cost of the energy system ($\mathbf{C}_{tot}$), defined as the sum of the annualized investment cost of the technologies ($\tau \mathbf{C}_{inv}$), the operating and maintenance cost of the technologies ($\mathbf{C}_{maint}$) and the operating cost of the resources ($\mathbf{C}_{op}$). The total investment cost ($\mathbf{C}_{inv}$) of each technology results from the multiplication of its specific investment cost (c_{inv}) and its installed size ($\mathbf{F}$), the latter defined with respect to the main end-uses output⁴ type, Eq. (2.3). $\mathbf{C}_{inv}$ is annualised with the factor τ , calculated based on the interest rate (i_{rate}) and the technology lifetime ($lifetime$), Eq. (2.2). The total operation and maintenance cost is calculated in the same way, Eq. (2.4). The total cost of the resources is calculated as the sum of the end-use over different periods multiplied by the period duration (t_{op}) and the specific cost of the resource (c_{op}), Eq. (2.5). Note that, in Eq. (2.5), summing over the typical days using the set T_H_TD ⁵

⁴Indeed, some technologies have several outputs, such as a cogeneration of heat and power. Thus, the installed size must be defined with respect to one of these outputs. As an example, CHP are defined based on the thermal output rather than the electrical one.

⁵To simplify the reading, the formulation $t \in T | \{h, td\} \in T_H_TD(t)$ is used. However, this cannot be directly implemented in the code and it requires two additional sets: $HOUR_OF_PERIOD(t)$ and $TYPICAL_DAY_OF_PERIOD(t)$.

is equivalent to summing over the 8760h of the year.

$$\mathbf{GWP}_{\text{tot}} = \sum_{j \in \text{TECH}} \frac{\mathbf{GWP}_{\text{constr}}(j)}{\text{lifetime}(j)} + \sum_{i \in \text{RES}} \mathbf{GWP}_{\text{op}}(i)$$

$$\left(\text{in this version of the model : } \mathbf{GWP}_{\text{tot}} = \sum_{i \in \text{RES}} \mathbf{GWP}_{\text{op}}(i) \right) \quad (2.6)$$

$$\mathbf{GWP}_{\text{constr}}(j) = gwp_{\text{constr}}(j) \mathbf{F}(j) \quad \forall j \in \text{TECH} \quad (2.7)$$

$$\mathbf{GWP}_{\text{op}}(i) = \sum_{t \in T | \{h, td\} \in T_H_TD(t)} gwp_{\text{op}}(i) \mathbf{F}_t(i, h, td) t_{\text{op}}(h, td) \quad \forall i \in \text{RES} \quad (2.8)$$

The global annual GHG emissions are calculated using a life cycle assessment (LCA) approach, i.e. taking into account emissions of the technologies and resources ‘*from cradle to grave*’. For climate change, the natural choice as indicator is the GWP, expressed in ktCO₂-eq./year. In Eq. (2.6), the total yearly emissions of the system ($\mathbf{GWP}_{\text{tot}}$) are defined as the sum of the emissions related to the construction and end-of-life of the energy conversion technologies ($\mathbf{GWP}_{\text{constr}}$), allocated to one year based on the technology lifetime (*lifetime*), and the emissions related to resources ($\mathbf{GWP}_{\text{op}}$). Similarly to the costs, the total emissions related to the construction of technologies are the product of the specific emissions (gwp_{constr}) and the installed size ($\mathbf{F}$), Eq. (2.7). The total emissions of the resources are the emissions associated to fuels (from cradle to combustion) and imports of electricity (gwp_{op}) multiplied by the period duration (t_{op}), Eq. (2.8). GWP accounting can be conducted in different manners and will be discussed in more detail later (see Section 4.1.3). The European Commission and the International Energy Agency (IEA) mainly uses resource-related emissions ($\mathbf{GWP}_{\text{op}}$) while neglecting indirect emissions related to the construction of technologies ($\mathbf{GWP}_{\text{constr}}$). To facilitate the comparison with their results, a similar implementation is proposed in Eq. (2.6).

System design and operation

$$f_{\min}(j) \leq \mathbf{F}(j) \leq f_{\max}(j) \quad \forall j \in \text{TECH} \quad (2.9)$$

The installed capacity of a technology ($\mathbf{F}$) is constrained between upper and lower bounds ($f_{\max}$ and $f_{\min}$), Eq. (2.9). This formulation allows accounting for old technologies still existing in the target year (lower bound), but also for the maximum deployment potential of a technology. As an example, for offshore wind turbines, $f_{\min}$ represents the existing installed capacity (which will still be available in the future), while $f_{\max}$ represents the maximum potential.

Hence, we have: $t \in T | \{h, td\} \in T_H_TD(t)$, which is equivalent in the code to $t \in T | h \in \text{HOUR_OF_PERIOD}(t), td \in \text{TYPICAL_DAY_OF_PERIOD}(t)$.

$$\mathbf{F}_t(j, h, td) \leq \mathbf{F}(j) c_{p,t}(j, h, td) \quad \forall j \in TECH, \forall h \in H, \forall td \in TD \quad (2.10)$$

$$\sum_{t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j, h, td) t_{op}(h, td) \leq \mathbf{F}(j) c_p(j) \sum_{t \in T | \{h, td\} \in T_H_TD(t)} t_{op}(h, td) \quad \forall j \in TECH \quad (2.11)$$

$$\sum_{t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(i, h, td) t_{op}(h, td) \leq avail(i) \quad \forall i \in RES \quad (2.12)$$

The operation of resources and technologies in each period is determined by the decision variable $\mathbf{F}_t$. The capacity factor of technologies is conceptually divided into two components: a capacity factor for each period ($c_{p,t}$) depending on resource availability (e.g. renewables) and a yearly capacity factor (c_p) accounting for technology downtime and maintenance. For a given technology, the definition of only one of these two is needed, the other one being fixed to the default value of 1. For example, intermittent renewables are constrained by an hourly load factor ($c_{p,t} \in [0; 1]$) while CCGTs are constrained by an annual load factor (c_p , in that case 96% in 2035). Eqs. (2.10) and (2.11) link the installed size of a technology to its actual use in each period (F_t) via the two capacity factors. The total use of resources is limited by the yearly availability (*avail*), Eq. (2.12).

$$\sum_{i \in RES \cup TECH \setminus STO} f(i, l) \mathbf{F}_t(i, h, td) + \sum_{j \in STO} \left(\mathbf{Sto}_{out}(j, l, h, td) - \mathbf{Sto}_{in}(j, l, h, td) \right) - \mathbf{EndUses}(l, h, td) = 0$$

$$\forall l \in L, \forall h \in H, \forall td \in TD \quad (2.13)$$

The matrix f defines for all technologies and resources outputs to (positive) and inputs (negative) layers. Eq. (2.13) expresses the balance for each layer: all outputs from resources and technologies (including storage) are used to satisfy the EUD or as inputs to other resources and technologies.

Storage

$$\mathbf{Sto}_{level}(j, t) = \mathbf{Sto}_{level}(j, t-1) \cdot (1 - \%_{sto_{loss}}(j)) +$$

$$t_{op}(h, td) \cdot \left(\sum_{l \in L | \eta_{sto,in}(j, l) > 0} \mathbf{Sto}_{in}(j, l, h, td) \eta_{sto,in}(j, l) - \sum_{l \in L | \eta_{sto,out}(j, l) > 0} \mathbf{Sto}_{out}(j, l, h, td) / \eta_{sto,out}(j, l) \right)$$

$$\forall j \in STO, \forall t \in T | \{h, td\} \in T_H_TD(t) \quad (2.14)$$

$$\mathbf{Sto}_{level}(j, t) = \mathbf{F}_t(j, h, td) \quad \forall j \in STO \text{ DAILY}, \forall t \in T | \{h, td\} \in T_H_TD(t) \quad (2.15)$$

$$\mathbf{Sto}_{level}(j, t) \leq \mathbf{F}(j) \quad \forall j \in STO \setminus STO \text{ DAILY}, \forall t \in T \quad (2.16)$$

The storage level ($\mathbf{Sto}_{level}$) at a time step (t) is equal to the storage level at $t-1$ (accounting for the

losses in $t - 1$), plus the inputs to the storage, minus the output from the storage (accounting for input/output efficiencies), Eq. (2.14). The storage systems which can only be used for short-term (daily) applications are included in the daily storage set (STO DAILY). For these units, Eq. (2.15) imposes that the storage level be the same at the end of each typical day⁶. Adding this constraint drastically reduces the computational time. For the other storage technologies, which can also be used for seasonal storage, the capacity is bounded by Eq. (2.16). For these units, the storage behaviour is thus optimized over 8760h.

$$\mathbf{Sto}_{in}(j, l, h, td) \cdot ([\eta_{sto,in}(j, l)] - 1) = 0 \quad \forall j \in STO, \forall l \in L, \forall h \in H, \forall td \in TD \quad (2.17)$$

$$\mathbf{Sto}_{out}(j, l, h, td) \cdot ([\eta_{sto,out}(j, l)] - 1) = 0 \quad \forall j \in STO, \forall l \in L, \forall h \in H, \forall td \in TD \quad (2.18)$$

$$\begin{aligned} (\mathbf{Sto}_{in}(j, l, h, td) t_{sto,in}(j) + \mathbf{Sto}_{out}(j, l, h, td) t_{sto,out}(j)) &\leq \mathbf{F}(j) \%_{sto,avail}(j) \\ \forall j \in STO, \forall l \in L, \forall h \in H, \forall td \in TD \end{aligned} \quad (2.19)$$

Eqs. (2.17)-(2.18) force the power input and output to zero if the layer is incompatible⁷. As an example, a PHS will only be linked to the electricity layer (input/output efficiencies > 0). All other efficiencies will be equal to 0, to impede that the PHS exchanges with incompatible layers (e.g. mobility, heat, etc). Eq. (2.19) limits the power input/output of a storage technology based on its installed capacity ($\mathbf{F}$) and three specific characteristics. First, storage availability ($\%_{sto,avail}$) is defined as the ratio between the available storage capacity and the total installed capacity (default value is 100%). This parameter is only used to realistically represent V2G, for which we assume that only a fraction of the fleet (i.e. 20% in these cases) can charge/discharge at the same time. Second and third, the charging/discharging time ($t_{sto,in}$, $t_{sto,out}$), which are the time to complete a full charge/discharge from empty/full storage⁸. As an example, a daily thermal storage needs at least 4 hours to discharge ($t_{sto,out} = 4[h]$), and another 4 hours to charge ($t_{sto,in} = 4[h]$).

Networks

$$\begin{aligned} \mathbf{Net}_{loss}(eut, h, td) &= \left(\sum_{i \in RES \cup TECH \setminus STO | f(i, eut) > 0} f(i, eut) \mathbf{F}_t(i, h, td) \right) \%_{net,loss}(eut) \\ \forall eut &= EUT, \forall h \in H, \forall td \in TD \end{aligned} \quad (2.20)$$

⁶In most cases, the activation of the constraint stated in Eq. (2.14) will have as a consequence that the level of storage be the same at the beginning and at the end of each day — hence the use of the terminology ‘daily storage’. Note, however, that such daily storage behaviour is not always guaranteed by this constraint and thus, depending on the typical days sequence, a daily storage behaviour might need to be explicitly enforced.

⁷In the code, these equations are implemented with a *if-then* statement.

⁸In this linear formulation, storage technologies can charge and discharge at the same time. On the one hand, this avoids the need of integer variables; on the other hand, it has no physical meaning. However, in a cost minimization problem, the cheapest solution identified by the solver will always choose to either charge or discharge at any given t , as long as cost and efficiencies are defined. Hence, we recommend to always verify numerically the fact that only storage inputs or outputs are activated at each t , as we do in all our implementations.

$$\mathbf{F}(\text{Grid}) = 1 + \frac{c_{\text{grid},\text{extra}}}{c_{\text{inv}}(\text{Grid})} \left(\mathbf{F}(\text{Wind}_{\text{onshore}}) + \mathbf{F}(\text{Wind}_{\text{offshore}}) + \mathbf{F}(\text{PV}) - (f_{\min}(\text{Wind}_{\text{onshore}}) + f_{\min}(\text{Wind}_{\text{offshore}}) + f_{\min}(\text{PV})) \right) \quad (2.21)$$

$$\mathbf{F}(\text{DHN}) = \sum_{j \in \text{TECH OF EUT}(\text{HeatLowTDHN})} \mathbf{F}(j) \quad (2.22)$$

Eq. (2.20) calculates network losses as a share ($\%_{\text{net}_{\text{loss}}}$) of the total energy transferred through the network. As an example, losses in the electricity grid are estimated to be 4.5% of the energy transferred in 2015⁹. Eqs. (2.21)-(2.22) define the extra investment for networks. Integration of intermittent RE implies additional investment costs for the electricity grid ($c_{\text{grid},\text{extra}}$). As an example, the reinforcement of the electricity grid is estimated to be 358 millions €₂₀₁₅ per Gigawatt of intermittent renewable capacity installed (see Appendix C.3.6 for details). Eq. (2.22) links the size of DHN to the total size of the installed centralized energy conversion technologies.

Additional Constraints

$$\mathbf{F}_t(\text{Nuclear}, h, td) = \mathbf{P}_{\text{Nuclear}} \quad \forall h \in H, \forall td \in TD \quad (2.23)$$

Nuclear power plants are assumed to have no power variation over the year, Eq. (2.23). If needed, this equation can be replicated for all other technologies for which a constant operation over the year is desired.

$$\mathbf{F}_t(j, h, td) = \%_{\text{PassMob}}(j) \sum_{l \in \text{EUT of EUC}(\text{PassMob})} \mathbf{EndUses}(l, h, td) \quad \forall j \in \text{TECH OF EUC}(\text{PassMob}), \forall h \in H, \forall td \in TD \quad (2.24)$$

$$\mathbf{F}_t(j, h, td) = \%_{\text{FreightMob}}(j) \sum_{l \in \text{EUT of EUC}(\text{FreightMob})} \mathbf{EndUses}(l, h, td) \quad \forall j \in \text{TECH OF EUC}(\text{FreightMob}), \forall h \in H, \forall td \in TD \quad (2.25)$$

$$\%_{\text{Fr,Rail}} + \%_{\text{Fr,Train}} + \%_{\text{Fr,Boat}} = 1 \quad (2.26)$$

Eqs. (2.24)-(2.25) impose that the share of the different technologies for mobility ($\%_{\text{PassMob}}$) and ($\%_{\text{Freight}}$) be the same at each time step¹⁰. In other words, if 20% of the mobility is supplied by train, this share remains constant in the morning or the afternoon. Eq. (2.26) verifies that the freight technologies supply the overall freight demand (this constraint is related to Figure 2.8).

⁹This is the ratio between the losses in the grid and the total annual electricity production in Belgium in 2015 [92].

¹⁰All equations expressed in a compact non-linear form in this section Eqs. (2.24), (2.25), (2.29) and (2.33)) can be linearised. For these cases, the **EndUses** is defined with parameters and a variable representing a constant share over the year (e.g. $\%_{\text{public}}$). As an example, **EndUses** in Eq. (2.24) is equal to **EndUsesInput**(*PassMb*) · $\%_{\text{pass}}(h, td) / t_o p(h, td)$. The term $\%_{\text{public}}$, is missing in the equation, but is implicitly implemented in $\%_{\text{PassMob}}$.

Decentralised heat production

$$\mathbf{F}(Dec_{Solar}) = \sum_{j \in TECH\ OF\ EUT(HeatLowTDec) \setminus \{Dec_{Solar}\}} \mathbf{F}_{sol}(j) \quad (2.27)$$

$$\mathbf{F}_{t_{sol}}(j, h, td) \leq \mathbf{F}_{sol}(j) c_{p,t}(Dec_{Solar}, h, td) \\ \forall j \in TECH\ OF\ EUT(HeatLowTDec) \setminus \{Dec_{Solar}\}, \forall h \in H, \forall td \in TD \quad (2.28)$$

Thermal solar is implemented as a decentralized technology. It is always installed together with another decentralized technology, which serves as backup to compensate for the intermittency of solar thermal. Thus, we define the total installed capacity of solar thermal $\mathbf{F}(Dec_{Solar})$ as the sum of $\mathbf{F}_{sol}(j)$, Eq. (2.27), where $\mathbf{F}_{sol}(j)$ is the solar thermal capacity associated to the backup technology j . Eq. (2.28) links the installed size of each solar thermal capacity ($\mathbf{F}_{sol}(j)$) to its actual production ($\mathbf{F}_{t_{sol}}(j, h, td)$) via the solar capacity factor ($c_{p,t}(Dec_{Solar}, h, td)$).

$$\mathbf{F}_t(j, h, td) + \mathbf{F}_{t_{sol}}(j, h, td) + \sum_{l \in L} (\mathbf{Sto}_{out}(i, l, h, td) - \mathbf{Sto}_{in}(i, l, h, td)) \\ = \%HeatDec(j) \mathbf{EndUses}(HeatLowT, h, td) \\ \forall j \in TECH\ OF\ EUT(HeatLowTDec) \setminus \{Dec_{Solar}\}, i \in TS\ OF\ DEC\ TECH(j), \forall h \in H, \forall td \in TD \quad (2.29)$$

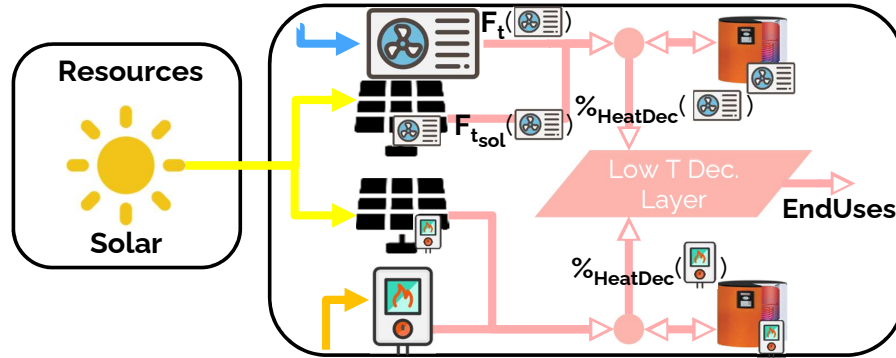


Figure 2.9 – Illustrative example of a decentralised heating layer with thermal storage, solar thermal and two conventional production technologies, gas boilers and electrical HP. In this case, Eq. (2.29) applied to the electrical HPs becomes the equality between the two following terms: left term is the heat produced by: the eHPs ($\mathbf{F}_t('eHPs')$), the solar panel associated to the eHPs ($\mathbf{F}_{t_{sol}}('eHPs')$) and the storage associated to the eHPs; right term is the product between the share of decentralised heat supplied by eHPs ($\%HeatDec('eHPs')$) and heat low temperature decentralised demand ($\mathbf{EndUses}(HeatLowT, h, td)$).

A thermal storage i is defined for each decentralised heating technology j , to which it is related via the set $TS\ OF\ DEC\ TECH$, i.e. $i = TS\ OF\ DEC\ TECH(j)$. Each thermal storage i can store heat from its technology j and the associated thermal solar $\mathbf{F}_{sol}(j)$. Similarly to the passenger mobility, Eq. (2.29)

makes the model more realistic by defining the operating strategy for decentralized heating. In fact, in the model we represent decentralized heat in an aggregated form; however, in a real case, residential heat cannot be aggregated. A house heated by a decentralised gas boiler and solar thermal panels should not be able to be heated by the electrical heat pump and thermal storage of the neighbours, and vice-versa. Hence, Eq. (2.29) imposes that the use of each technology ($F_t(j, h, td)$), plus its associated thermal solar ($F_{t_{sol}}(j, h, td)$) plus its associated storage outputs ($Sto_{out}(i, l, h, td)$) minus its associated storage inputs ($Sto_{in}(i, l, h, td)$) should be a constant share ($\%HeatDec(j)$) of the decentralised heat demand ($EndUses(HeatLowT, h, td)$). Figure 2.9 shows, through an example with two technologies (a gas boiler and a HP), how decentralised thermal storage and thermal solar are implemented.

Vehicle-to-grid

$$F(i) = \frac{F(j)}{veh_{capa}(j)} ev_{batt,size}(j) \quad \forall j \in V2G, i \in EVs_BATT\ OF\ V2G(j) \quad (2.30)$$

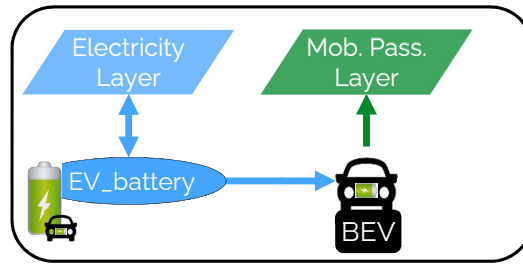


Figure 2.10 – Illustrative example of a V2G implementation. The battery can interact with the electricity layer. The V2G takes the electricity from the battery to provide a constant share ($\%PassMob$) of the passenger mobility layer (*Mob. Pass.*).

Vehicle-to-grid dynamics are included in the model via the $V2G$ set. For each vehicle $j \in V2G$, a battery i ($i \in EVs_BATT$) is associated using the set $EVs_BATT\ OF\ V2G$ ($i \in EVs_BATT\ OF\ V2G(j)$). Each type j of $V2G$ has a different size of battery per car ($ev_{batt,size}(j)$), e.g. the first generation battery of the Nissan Leaf (ZE0) has a capacity of 24 kWh¹¹. The number of vehicles of a given technology is calculated with the installed capacity (F) in [km-pass/h] and its capacity per vehicles (veh_{capa} in [km-pass/h/veh.]). Thus, the energy that can be stored in batteries $F(i)$ of $V2G(j)$ is the ratio of the installed capacity of vehicle by its specific capacity per vehicles times the size of battery per car ($ev_{batt,size}(j)$), Eq. (2.30). As an example, if this technology of cars covers 10 Mpass-km/h, and the capacity per vehicle is 50.4 pass-km/car/h (which represents an average speed of 40km/h and occupancy of 1.26 passenger per car); thus, the amount of battery electric vehicle (BEV) cars are 0.198 million cars. And if a BEV has a 24kWh of battery, such as the Nissan Leaf (ZE0), thus, the

¹¹This generation (ZE0) was marketed from 2010 to 2017 with a battery capacity of 24 kWh. The new generation (ZE1) accounts for an improved capacity and reaches 40 kWh per battery. Data from https://en.wikipedia.org/wiki/Nissan_Leaf, consulted on 08-02-2021

equivalent battery has a capacity of 4.76 GWh. However, the full capacity of electric vehicles cannot be used to support the grid, as all the cars won't be connected at the same time. This is constrained by the storage availability ($\%_{sto_{avail}}$) and has a typical value of 20% for BEV, see Eq. (2.19).

$$\mathbf{Sto}_{out}(i, Elec, h, td) \geq -f(j, Elec)\mathbf{F}_t(j, h, td) \quad \forall j \in V2G, \forall i \in EVs_BATT \text{ OF } V2G(j), \forall h \in H, td \in TD \quad (2.31)$$

Eq. (2.31) forces batteries of electric vehicles to supply, at least, the energy required by each associated electric vehicle technology. This lower bound is not an equality; in fact, according to the V2G concept, batteries can also be used to support the grid. Figure 2.10 shows through an example with only BEVs how Eq. (2.31) simplifies the implementation of V2G. In this illustration, a battery technology is associated to a BEV. The battery can either supply the BEV needs or sends electricity back to the grid.

Peak demand

$$\mathbf{F}(j) \geq \%_{Peak_{sh}} \max_{h \in H, td \in TD} \{\mathbf{F}_t(j, h, td)\} \quad \forall j \in TECH \text{ OF } EUT(HeatLowTDEC) \setminus \{Dec_{Solar}\} \quad (2.32)$$

$$\sum_{j \in TECH \text{ OF } EUT(HeatLowTDHN), i \in STO \text{ OF } EUT(HeatLowTDHN)} \left(\mathbf{F}(j) + \mathbf{F}(i) / t_{sto_{out}}(i, HeatLowTDHN) \right) \geq \%_{Peak_{sh}} \max_{h \in H, td \in TD} \{\mathbf{EndUses}(HeatLowTDHN, h, td)\} \quad (2.33)$$

Finally, Eqs. (2.32)-(2.33) constrain the installed capacity of low temperature heat supply. Based on the selected TDs, the ratio between the yearly peak demand and the TDs peak demand is defined for space heating ($\%_{Peak_{sh}}$). Eq. (2.32) imposes that the installed capacity for decentralised technologies covers the real peak over the year. Similarly, Eq. (2.33) forces the centralised heating system to have a supply capacity (production plus storage) higher than the peak demand. These equations force the installed capacity to meet the peak heating demand, i.e. which represents, somehow, the network adequacy¹².

¹²The model resolution of the dispatch is not accurate enough to verify the adequacy. As one model cannot address all the issues, another approach has been preferred: couple the model to a dispatch one, and iterate between them. Percy and Coates [93] demonstrated the feasibility of coupling a design model (EnergyScope TD) with a dispatch one (Dispa-SET [39]). Based on a feedback loop, they iterated on the design to verify the power grid adequacy and the strategic reserves. Results show that the backup capacities and storage needed to be slightly increased compared to the results of the design model alone.

Adaptations for the case study

Additional constraints are required to implement scenarios. Scenarios require six additional constraints (Eqs. (2.34)-(2.39)) to impose a limit on the GWP emissions, the minimum share of RE primary energy, the relative shares of technologies, such as gasoline cars in the private mobility, the cost of energy efficiency measures, the electricity import power capacity and the available surface area for solar technologies.

$$\mathbf{GWP}_{\text{tot}} \leq \text{gwp}_{\text{limit}} \quad (2.34)$$

$$\sum_{j \in \text{RES}_{\text{re}}, t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j, h, td) \cdot t_{op}(h, td) \geq \text{re}_{\text{share}} \sum_{j \in \text{RES}, t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j, h, td) \cdot t_{op}(h, td) \quad (2.35)$$

To force the Belgian energy system to decrease its emissions, two lever can constraint the annual emissions: Eq. (2.34) imposes a maximum yearly emissions threshold on the GWP ($\text{gwp}_{\text{limit}}$); and Eq. (2.35) fixes the minimum renewable primary energy share.

$$\begin{aligned} f_{\min, \%}(j) \sum_{j' \in \text{TECH OF EUT}(eut), t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j', h, td) \cdot t_{op}(h, td) &\leq \sum_{j \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j, h, td) \cdot t_{op}(h, td) \\ &\leq f_{\max, \%}(j) \sum_{j'' \in \text{TECH OF EUT}(eut), t \in T | \{h, td\} \in T_H_TD(t)} \mathbf{F}_t(j'', h, td) \cdot t_{op}(h, td) \\ &\quad \forall eut \in \text{EUT}, \forall j \in \text{TECH OF EUT}(eut) \end{aligned} \quad (2.36)$$

To represent the Belgian energy system in 2015, Eq. (2.36) imposes the relative share of a technology in its sector. Eq. (2.36) is complementary to Eq. (2.9), as it expresses the minimum ($f_{\min, \%}$) and maximum ($f_{\max, \%}$) yearly output shares of each technology for each type of EUD. In fact, for a given technology, assigning a relative share (e.g. boilers providing at least a given percentage of the total heat demand) is more intuitive and close to the energy planning practice than limiting its installed size. $f_{\min, \%}$ and $f_{\max, \%}$ are fixed to 0 and 1, respectively, unless otherwise indicated.

$$\mathbf{F}(\text{Efficiency}) = \frac{1}{1 + i_{\text{rate}}} \quad (2.37)$$

To account for efficiency measures from today to the target year, Eq. (2.37) imposes their cost. The EUD is based on a scenario detailed in Section 4.2.1 and has a lower energy demand than the “business as usual” scenario, which has the highest energy demand. Hence, the energy efficiency cost accounts for all the investment required to decrease the demand from the “business as usual” scenario and the implemented one. As the reduced demand is imposed over the year, the required investments must be completed before this year. Therefore, the annualisation cost has to be deducted from one year. This mathematically implies to define the capacity of efficiency measures

deployed to $1/(1 + i_{rate})$ rather than 1. The investment is already expressed in €_{2015} .

$$\mathbf{F}_t(\text{Electricity}, h, td) \leq elec_{import,max} \quad \forall h \in H, \forall td \in TD \quad (2.38)$$

Eq. (2.38) limits the power grid import capacity from neighbouring countries based on a net transfer capacity ($elec_{import,max}$).

$$\mathbf{F}(PV)/power_density_{pv} + (\mathbf{F}(Dec_{Solar}) + \mathbf{F}(DHN_{Solar}))/power_density_{solar\ thermal} \leq solar_area \quad (2.39)$$

In this model version, the upper limit for solar based technologies is calculated based on the available land area ($solar_area$) and power densities of both PV ($power_density_{pv}$) and solar thermal ($power_density_{solar\ thermal}$), Eq. (2.39). The equivalence between an install capacity (in watt peaks Wp) and the land use (in km^2) is calculated based on the power peak density ($[Wp/m^2]$). In other words, it represents the peak power of a one square meter of solar panel. We evaluate that PV and solar thermal have a power peak density of $power_density_{pv}=0.2367$ and $power_density_{solar\ thermal}=0.2857$ $[GW/km^2]$ ¹³. Thus, the land use of PV is the installed power ($\mathbf{F}(PV)$ in $[GW]$) divided by the power peak density (in $[GW/km^2]$). This area is a lower bound of the real installation used. Indeed, here, the calculated area correspond to the installed PV. However, in utility plants, panels are oriented perpendicular to the sunlight. As a consequence, a space is required to avoid shadow between rows of panels. In the literature, the *ground cover ratio* is defined as the total spatial requirements of large scale solar PV relative to the area of the solar panels. This ratio is estimated around five [96], which means that for each square meter of PV panel installed, four additional square meters are needed.

2.3 Implementation

The formulation of the MILP and LP problems has been implemented using an algebraic modeling language. The latter allows the representation of large LP and MILP problems. Its syntax is similar to a mathematical programming language (AMPL), which is - according to the NEOS-statistics¹⁴ - the most popular format for representing mathematical programming problems. The formulation enable the use of different solvers as open sources ones, such as GLPK, or commercial ones, such as CPLEX or Gurobi. In the code, each of the equations defined above is found as it is with the corresponding numbering. SETS, Variables and parameters have the same names (unless explicitly

¹³The calculation is based on the annual capacity factor, the conversion efficiency and the average yearly irradiation. As an example, for PV, the efficiency in 2035 is estimated at 23% [94] with an average daily irradiation - similar to historical values - of 2820 Wh/m^2 in Belgium [95]. The capacity factor of solar is around 11.4%, hence specific area for 1 kilowatt peak (kW_p) is $2820/24 \cdot 0.23/0.114 \approx 236.7 [MW_p/km^2] = 0.2367 [GW_p/km^2]$.

¹⁴NEOS Server is an Internet-based client-server application that provides free access to a library of optimization solvers, statistics are available at: <https://neos-server.org/neos/report.html>, consulted the 27/01/2021.

stated in the definition of the term). Figure 2.11 illustrates - for the balance constraint (Eq. (2.13)) - the mathematical formulation presented in this work and its implementation in the code. Colors highlight the same elements. In the implementation, each constraint has a comment (starting with #) and has a name (colored in black), in this case *layer_balance*. In addition, most of the SETS, Variables and parameters are more explicitly named, as a first example the set layers is named *L* in the paper and *LAYERS* in the implementation; or as another example, the input efficiency who is named *f* in the paper and *layers_in_out* in the implementation.

$$\sum_{i \in RES \cup TECH \setminus STO} f(i, l) F_t(i, h, td) + \sum_{j \in STO} \left(\text{Sto}_{out}(j, l, h, td) - \text{Sto}_{in}(j, l, h, td) \right) - \text{EndUses}(l, h, td) = 0$$

$\forall l \in L, \forall h \in H, \forall td \in TD$

```
# [Eq. 2.13] [...]
subject to layer_balance {l in LAYERS, h in HOURS, td in TYPICAL_DAYS}:
    sum {i in RESOURCES union TECHNOLOGIES diff STORAGE_TECH } layers_in_out[i, l] * F_t [i, h, td]
    + sum {j in STORAGE_TECH} ( Storage_out [j, l, h, td] - Storage_in [j, l, h, td] )
    - End_uses [l, h, td]
    = 0;
```

Figure 2.11 – Comparison of equation formulation (upper equation) and code implementation (lower figure). Example based on Eq. (2.13).

The entire implementation is available on the directory [69] and its architecture is illustrated in Figure 2.12. Four folders compose the repository and contain the documentation (Documentation), the data used (Data_management), the MILP implementation (STEP_1_TD_selection) and the LP implementation (STEP_2_Energy_Model). For each of the models, the definition of the terms (SETS, Variables and Parameters) as well as the domains of the variables, the formulation of the constraints and the objective function are included in the model file (with the extension .mod). The numerical values of the parameters are contained in separate files (with the extension .dat). Finally, the output data of the model are saved in a file (with the extension .out) or a folder (\outputs). An interface - via excel - allows to visualise the data (DATA.xlsx) and to generate the data files (STEP_1_in.xlsx, STEP_1_out.xlsx and STEP_2_in.xlsx). Finally, a user guide manual is available in the documentation to support the modeler in her/his first steps.

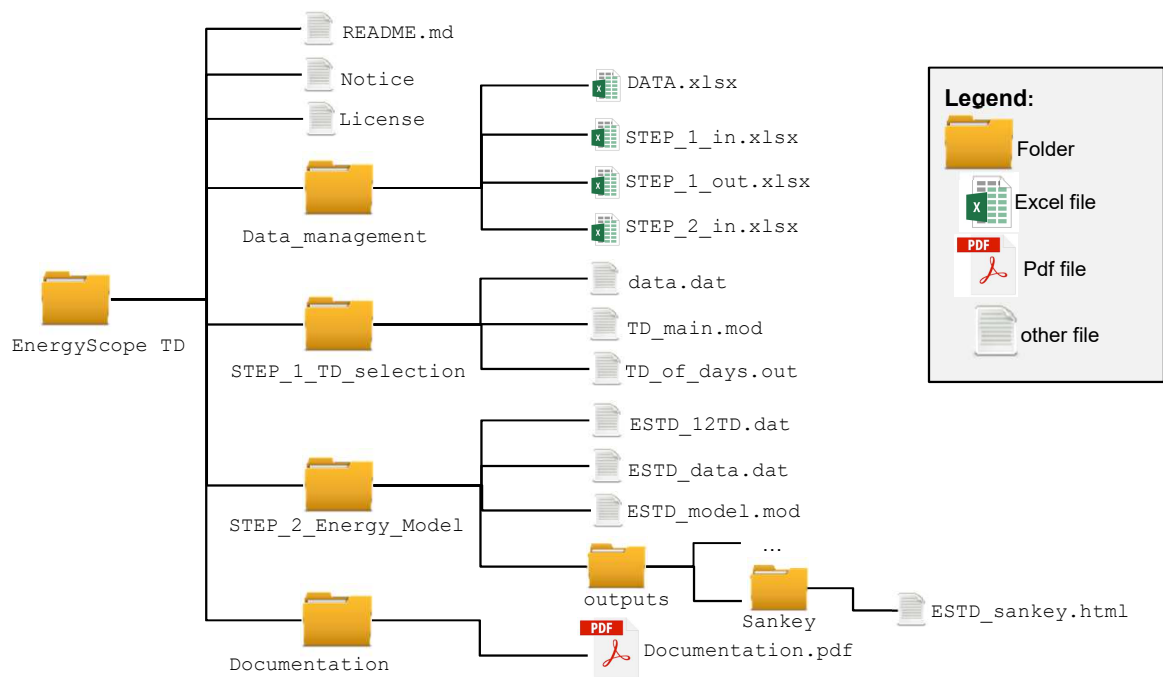
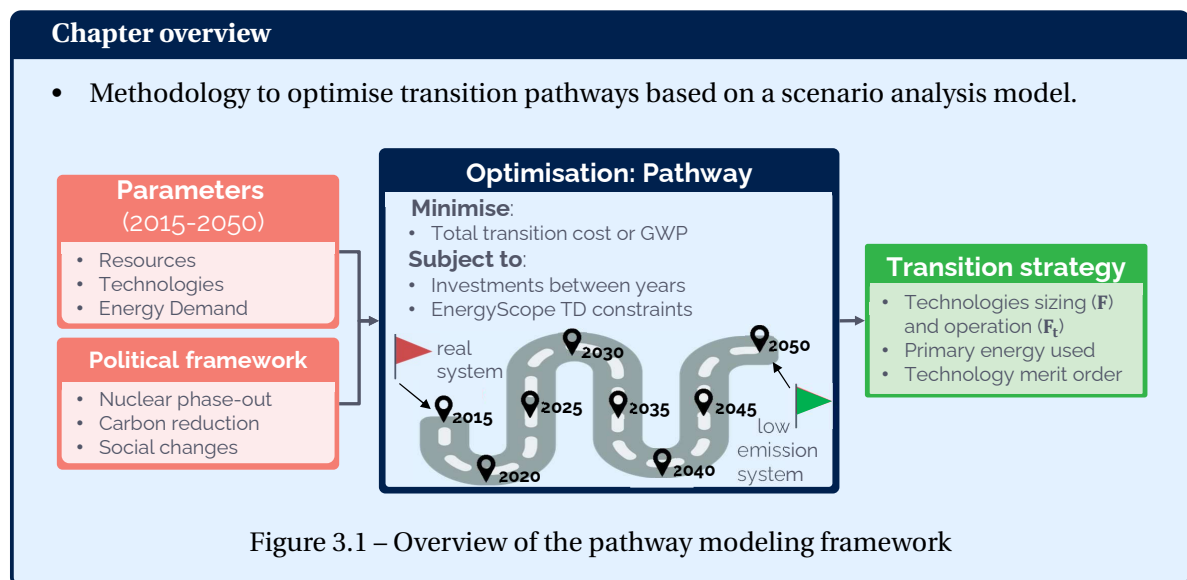


Figure 2.12 – EnergyScope TD repository structure available at [69].

3 Modelling for pathway analysis



In the previous chapter, the EnergyScope TD model was presented. It is tailored to analyse different scenarios, and it answers research questions such as: which resources are going to substitute fossil fuels? What is the most effective design to integrate intermittent renewables? Which technologies will play a major role? In a nutshell, EnergyScope TD model is a tool to better understand the long term target. Nevertheless, it doesn't indicate how to reach this target.

Defining the path from today energy system to a low emission one in 2050 is another challenge. The chosen strategy is to extend the EnergyScope TD model to an transition pathway one. As illustrated in the previous chapter, the presented model has a short computational time and accounts for the hourly operation over a year. In addition, its concise formulation makes it an appropriate candidate to be extended to a *pathway* model.

Challenges and research approach

To achieve this extension, there are four major challenges to be tackled: (i) how to manage different time scales (hours, years, decades)? (ii) how to implement ageing technologies? (iii) how to represent society's inertia to change? and, (iv) how to calculate costs and emissions over a long period of time.

The time horizon considered for the transition is from yesterday, 2015, to the European Commission's objective: carbon neutral by 2050. As previously motivated, an hourly resolution over a year is required to accurately estimate the storage capacity needs and how to integrate intermittent renewables. This problem will be addressed by applying the EnergyScope TD model to representative years.

Implementing technologies during the transition years brings many difficulties. Indeed, the price, efficiency, maintenance cost, etc. of technologies vary from year to year, how can this be taken into account? How to distinguish between technologies that reach their lifetime and those that are dismantled earlier? How to initialise the problem in 2015? This problem will be solved by making some simplifications and implementing new constraints.

A linear programming problem can vary from one year to the next without taking into account the society's inertia to change. However, even if the optimum is to switch exclusively to one technology, e.g. from gasoline and diesel cars to electric ones, this cannot be done in a few years. Thus, a representation of this inertia is required. The latter represents the acceptance of citizens to change technology, the training of competent people to install these technologies, the projects permitting, the time it takes for industries to put these new technologies into production, etc. In response to this problem, new constraints have been implemented to limit change in the sectors concerned.

One euro today is not equal to one euro tomorrow, just as a tonne of CO₂ emitted today will not have the same impact as one tonne emitted tomorrow. An accounting method has been developed to take into account this difference over the time horizon.

Contributions

In this chapter, we present the model called *EnergyScope pathway*, it optimises the investment strategies over the period 2015 to 2050. At the same time, the model optimises the hourly operation over representative years. To achieve this, the EnergyScope TD methodology is extended to the pathway version which accounts for new SETs, Variables, parameters, constraints and an adapted objective function.

The resulting model has to address four major challenges described previously and requiring to develop new methodologies. And more specifically in a linear formulation of equations that enable to account for the evolution of technologies over a period of 35 years, taking into account characteristics

that vary from year to year. But also in the formulation of equations representing the inertia of society.

Similarly to the EnergyScope TD version, the pathway version has a perfect foresight, and optimises all the transition design and operation at once. The minimised objective is the total cost of the transition.

3.1 Methodology

Modelling the energy transition involves representing the energy system from today to a low emission one. A representation of all the years is too cumbersome, so it is proposed to represent the energy system every 5 years from 2015 to 2050. Consequently, 8 years, later called representative years, are related. For each of these years, the EnergyScope TD model is applied with data updated, such as energy demand, technology costs, CO₂ emissions target. Figure 3.2 represents this methodology. It results in one large LP model which involves: eight resolutions of EnergyScope TD for the representative years (see blue boxes in Figure 3.2), and the design constraints between two consecutive years (see black boxes in Figure 3.2).

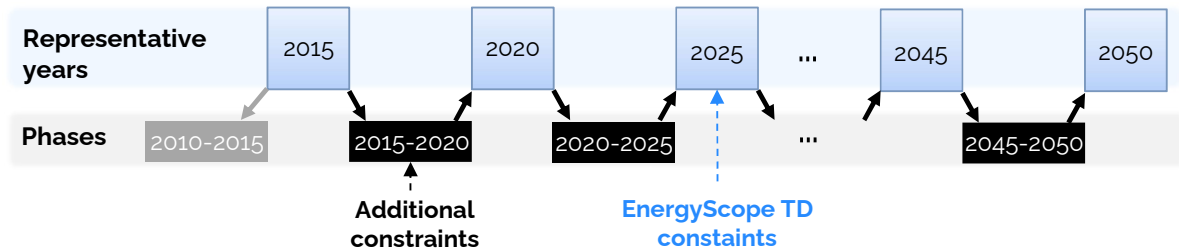


Figure 3.2 – Illustration of the Pathway methodology: EnergyScope TD is resolved over 8 representative years (blue boxes). In-between, a phase limit the design changes between consecutive years (black boxes). The problem is initialised in year 2015 (grey box).

At this stage, the transition is not correctly represented because there is no link between the years. Each representative year requires a mix of technologies which can vary from one representative year to another. To link them, additional constraints are necessary. Some compromises have been necessary, and are summarised through the following assumptions: the lifetime of a technology does not change during the transition (e.g. if the lifetime of a CCGT installed in 2015 is 25 years, then the same lifetime will be used for a CCGT installed in 2040); the efficiency is adapted from year to year, e.g. if a gas boiler is installed in 2015, it is assumed that it will have the efficiency of a new gas boiler in 2020¹; technologies that exist in 2015 are considered new, e.g. the 3.9 GW of CCGTs estimated in 2015 can be used until 2040²; the capacity installed is constant during a representative year but can vary between two of them. Based on these assumptions, a linear formulation - presented hereafter -

¹This assumption is required to ensure a linear formulation of Eq. (2.13).

²This assumption was made because the age of all the technologies in 2015 were not found. The impact of this

is defined based on four constraints, three variables, one set and one parameter. Similarly to the energy balance, a balance is made on the capacity installed between two representative years. For each technology, the capacity for the next representative year is equal to the one of the previous representative year plus the new capacity build, minus the capacity which reached its lifetime, minus capacity early decommissioned during the same period. We deem '*early decommissioned*', a technology that will be removed before it reaches its lifetime limit. A technology may be early decommissioned if it will not be used in the coming years (e.g. coal-based power plants).

To avoid unrealistic change between two representative years, the change made in three sectors are limited. The '*change*' accounts for the amount of energy service provided per technology in a sector, such as passenger-kilometers provided by gasoline cars in the passenger mobility sector. Thus, the proposed implementation avoid all the passenger mobility to switch from one technology (gasoline and diesel cars) to another (electric vehicles or buses). The three sectors are: passenger mobility, freight mobility, and low temperature heat. We assume that high temperature heat and electricity sectors can drastically change in 5 years. It results in four constraints, one per sectors plus one to define the *change* in each sector.

To optimise the energy system, two key metrics must be adapted: the transition cost and the total global warming potential (GWP). Concerning the first one, all costs are expressed in €₂₀₁₅ and an annualisation factor is used to distinguish investments over the transition. For the GWP, the metric used is based on the harmfulness of the gas over 100 years. It is assumed that the impact of emitting at the beginning or the end of transition are equivalent and thus no annualisation is made.

3.1.1 Additional sets, parameters and variables

To represent the new structure, the EnergyScope TD model is replicated for each representative year and phases will be defined in-between. As a consequence, a new dimension '*year*' is added to all Variables and parameters, except the interest rate (i_{rate}) assumed constant during the transition. This new dimension is necessary to represent the changes of technology characteristics over the representative years. As an example, the investment cost of a battery will drastically vary between 2020 and 2035 (from 501 to 302 [€₂₀₁₅/kWh]). Consequently, new SETs, parameters and Variables are defined and summarised in Tables 3.1, 3.2 and 3.3, respectively.

3.1.2 Pathway formulation

Hereafter, we present the new constraints (Eqs. (3.1)-(3.17)) defined to create the link between consecutive years and address the four challenges raised.

assumption is little as the design in 2015 in 2015 is imposed - and thus the investments - for all scenarios, and that technologies can be removed prematurely (e.g. nuclear in 2020 and 2025).

Table 3.1 – New SETs for pathway formulation.

Set	Index	Description
YEARS	$y \in Y$	Representative years when the EnergyScope TD model is evaluated
PHASE	$p \in P$	Phase between two consecutive YEARS
PHASE_START (p) $\subset Y$		Year just before the phase p
PHASE_STOP (p) $\subset Y$		Year just after the phase p
AGE ($tech, p$) $\subset P \cup \text{Exceptions}^a$		Phase when the technology ($tech$) has been built

^aThe set AGE gives for each technology ($tech$) at a phase (p) the phase when it has been built. However, the set PHASE does not cover all the cases. Instead, if the technology has been built before YEAR_2015, another value is assigned to the set AGE. Either the technology has been built just the phase before YEAR_2015 (“2010_2015”) or the technology has been built before (“STILL_IN_USE”). Section 3.1.2 illustrates the use of this parameter.

Table 3.2 – New parameters for pathway formulation. Set indices as in Figure 2.7

Parameter	Units	Description
$max_{inv, phase}(p)$	[€ ₂₀₁₅]	Maximum investment per phase
t_{phase}	[y]	Phase period (default 5 years) ^a
$diff_{2015, phase}(p)$	[y]	Years difference between financial reference year (2015) and the phase ^b .
$gwp_{limit, transition}$	[ktCO ₂]	Maximum CO _{2eq} emissions during the transition.
$decom_{allowed}(p, p, tech)$	[-]	Allow a technology to be decommissioned ^c
$limit_{LT, renovation}$	[-]	Limit the change in low-temperature heat technologies during a phase ^d
$limit_{pass. mob, changes}$	[-]	Limit the change in passenger mobility technologies during a phase ^d
$limit_{freight, changes}$	[-]	Limit the change in freight mobility technologies during a phase ^d
$efficiency(y)$	[-]	Share of energy efficiency achievement compared to reference (2050).
$\tau_{phase}(p)$	[-]	Annualisation factor

^aIn this Pathway version, two time scales are mentioned, the one used by the EnergyScope TD model to evaluate the energy system (t_{op}), usually an hour; and the one for the transition between two representative years (t_{phase}), usually 5 years.

^bThis parameter is only used to evaluate the annualisation factor, see Eq. (3.8).

^cWhen in a period, the decommissioning is not allowed ($decom_{allowed} = 0$), the variable (**F_{decom}**) is forced to 0. See illustrations in Section 3.1.2.

^dA 20% value allows 20% of the service provided by the sectors' technologies to change during a phase. As an example, for private mobility, this means that over a period 20% of the passenger mobility provided by one or more technologies may change; if 35% of the mobility is provided by gasoline car, after one period it can drop down to 15%.

Chapter 3. Modelling for pathway analysis

Table 3.3 – New variables for pathway formulation. All variables are continuous and non-negative, unless otherwise indicated.

Variable	Units	Description
$F_{\text{new}}(p^a, \text{tech})$	[GW] ^{bc}	Installed capacity during a phase with respect to the main output
$F_{\text{decom}}(p, p^a, \text{tech})$	[GW] ^{bc}	Decommissioned ^d capacity during a phase with respect to the main output
$F_{\text{old}}(p, \text{tech})$	[GW] ^{bc}	Retired ^d capacity during a phase with respect to the main output
$C_{\text{inv,phase}}(p)$	[M€/GW] ^e	Phase total annualised investment cost
$C_{\text{opex}}(y)$	[M€/GW] ^e	Operational expenditure over a year
$C_{\text{tot,opex}}$	[M€/GW] ^e	Total operational expenditure over the transition
$C_{\text{tot,capex}}$	[M€/GW] ^e	Total capital expenditure over the transition
$C_{\text{tot,trans}}$	[M€/GW] ^e	Total transition cost
$GWP_{\text{tot,trans}}$	[MtCO ₂]	Total transition global warming potential
$\Delta_{\text{change}}(p, \text{tech})$	[GW] ^{bc}	Change in a technology used during a phase

^a $p \in \text{PHASE} \cup \{2010_2015\}$.

^b [Mpkm] (millions of passenger-km) for passenger, [Mtkm] (millions of ton-km) for freight mobility end-uses

^c [GWh] if $\text{tech} \in \text{STO}$

^d During a phase, a technology can be retired (F_{old}) or decommissioned (F_{decom}). The retirement happens once the technology reaches its expected lifetime limit. Instead, the decommissioning can happen in-between the construction phase and the retirement.

^e [Mpkm] (millions of passenger-km) for passenger, [Mtkm] (millions of ton-km) for freight mobility end-uses, [GWh] if $\text{tech} \in \text{STO}$.

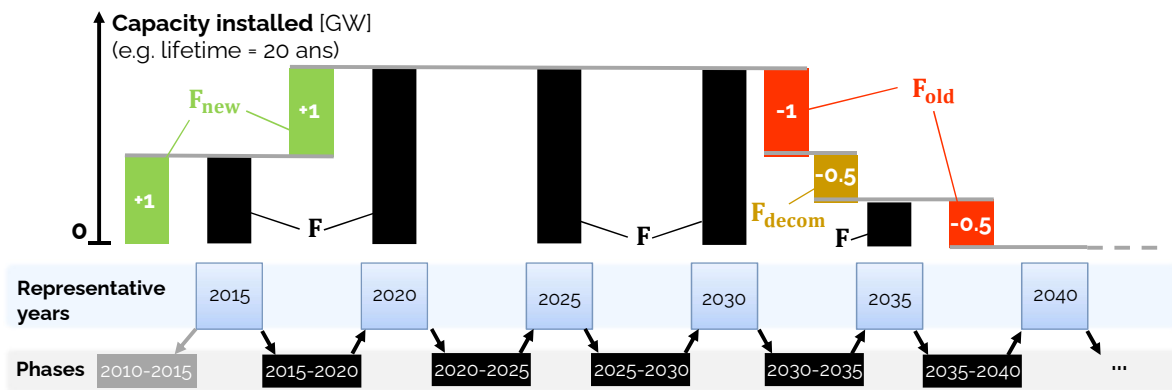


Figure 3.3 – Illustration of the new variables of the pathway version. Example based on a technology with a 20 years lifetime. Initially 1 GW of capacity exists (F_{new} during phase 2010_2015). Then another 1 GW is deployed (F_{new} during phase 2015_2020). 15 years later, a part of the capacity reaches its lifetime limit and is removed (F_{old} phase 2030_2035). Moreover, during the latter phase, additional capacity is decommissioned prematurely (F_{decom}). Finally, the technology reaches its expected lifetime and is fully withdrawn (F_{old}).

Technology changes

$$\mathbf{F}(y_{\text{stop}}, i) = \mathbf{F}(y_{\text{start}}, i) + \mathbf{F}_{\text{new}}(p, i) - \mathbf{F}_{\text{old}}(p, i) - \sum_{p2 \in \text{PHASE} \cup \{2010_2015\}} \mathbf{F}_{\text{decom}}(p, p2, i)$$

$$\forall p \in \text{PHASE}, y_{\text{stop}} \in P_STOP(p), y_{\text{start}} \in P_START(p), i \in \text{TECH} \quad (3.1)$$

$$\mathbf{F}_{\text{decom}}(p, p2, i) = 0$$

$$\forall i \in \text{TECH}, p \in \text{PHASE}, p2 \in \text{PHASE} \cup \{2010_2015\} | \text{decom}_{\text{allowed}}(p, p2) = 0 \quad (3.2)$$

Figure 3.3 illustrates how a technology varies over the different representative years and phases. The available capacity must be adapted between 2 representative years. Similarly to a mass balance, Eq. (3.1) is the balance on the amount of technologies deployed. The constraint forces the installation or withdrawing of capacities between two representative years: at the end of the phase (y_{stop}), the available capacity is the one used in the next representative year ($\mathbf{F}(y_{\text{stop}})$). This capacity is equal to the one available in the previous representative year ($\mathbf{F}(y_{\text{start}})$) plus the new installed capacity ($\mathbf{F}_{\text{new}}$) minus the capacity that has reached its lifetime ($\mathbf{F}_{\text{old}}$) minus the early decommissioned capacity ($\mathbf{F}_{\text{decom}}$). To decommission a technology ($tech$), two information are required: the phase when it is decommissioned (p) and the phase when the decommissioned capacity has been built (p_{built}). This mathematical implementation allows a physical non-sense: the decommissioning of a technology which hasn't been built yet ($p < p_{\text{built}}$). To prevent it, Eq. (3.2) constrains in this case the decommissioning of this technology to zero. To do so, a parameter ($\text{decom}_{\text{allowed}}$) is defined *a priori* and is equal to 0 or 1 when decommissioning is not possible or possible, respectively.

$$\mathbf{F}_{\text{new}}(2010_2015, i) = \mathbf{F}(\text{YEAR_2015}, i) \quad \forall i \in \text{TECH} \quad (3.3)$$

$$\mathbf{F}_{\text{old}}(p, i) = \begin{cases} \text{if}(\text{age} = \text{"STILL_IN_USE"}) \text{ then } 0 \\ \text{else} \left(\mathbf{F}_{\text{new}}(\text{age}, i) - \sum_{p2 \in \text{PHASE}} \mathbf{F}_{\text{decom}}(p2, \text{age}, i) \right) \end{cases}$$

$$\forall p \in \text{PHASE}, \forall j \in \text{TECH} | \text{age} \in \text{AGE}(p, j) \quad (3.4)$$

To initialise the problem in 2015 with the existing design, an additional phase '2010_2015' is created. Eq. (3.3) requires that the capacity used in 2015 is installed in the previous phase. Eq. (3.4) defines the capacity reaching its lifetime limit at a certain phase. For each phase, a SET (AGE) is calculated "*a priori*" and indicates when the technology was built for a given phase. In the case the technology has already reached its lifetime limit, the SET (AGE) returns the phase when the technology has been built³. As an example, Figure 3.3 shows a 20 years lifetime technology with 1 GW of capacity installed before 2015. The technology ($tech$) can be used until 2030_2035 (i.e. $\text{age}(tech, 2030_2035) = \text{STILL_IN_USE}$),

³The equation seems more complex than the problem addressed. Nevertheless, the second part of the equation is needed to remove the capacity that could have been withdrawn before reaching its expected lifetime.

then it must be removed (i.e. $age(tech, 2030_2035) = 2010_2015$). Equally, in 2035_2040 the capacity built 20 years before must be removed ($age(tech, 2035_2040) = 2015_2020$), and so on.

Cost calculation

$$\min C_{tot,trans} = C_{tot,capex} + C_{tot,opex} \quad (3.5)$$

$$C_{tot,capex} = \sum_{j \in TECH} C_{inv}(2015, j) + \sum_{p \in PHASE} C_{inv,phase}(p) \quad (3.6)$$

$$C_{tot,opex} = C_{opex}(2015) + t_{phase} \cdot \tau_{phase}(p) \cdot \sum_{p \in PHASE | y_{start} \in P_START(p), y_{stop} \in P_STOP(p)} (C_{opex}(y_{start}) + C_{opex}(y_{stop})) / 2 \quad (3.7)$$

$$\tau_{phase}(p) = 1 / (1 + i_{rate})^{diff_2015_year(p)} \quad (3.8)$$

The objective function to be minimised is the total transition cost of the energy system ($C_{tot,trans}$), defined as the sum of the total capital expenditure (CAPEX) ($C_{tot,capex}$) and the operational expenditure (OPEX) ($C_{tot,opex}$), according to Eq. (3.5). The total CAPEX ($C_{tot,capex}$) is the sum of the initial investment in year 2015 (C_{inv}) and the investment during each phase ($C_{inv,phase}$), Eq. (3.6). These investments account for the installation and dismantlement costs of the technologies. The total OPEX ($C_{tot,opex}$) is the sum of the OPEX in 2015 and the annualised sum of the OPEX during each phase (C_{opex}), Eq. (3.7). During a phase, the system OPEX is the product of the annualised phase factor, defined in Eq. (3.8), and the arithmetic average of OPEX cost for the representative years before and after the phase.

$$C_{opex}(y) = \sum_{i \in TECH} C_{maint}(y, i) + \sum_{j \in RES} C_{op}(y, j) \quad \forall y \in YEARS \quad (3.9)$$

For each year, the yearly OPEX (C_{opex}) is the sum of the operating and maintenance costs of technologies (C_{maint}) and the operating cost of the resources (C_{op}), Eq. (3.9). To calculate the total operation and maintenance costs (C_{maint}) and the cost of the resources (C_{op}), their equations from the previous chapter (2.4-2.5) are used with an additional dimension: the year.

$$C_{inv,phase}(p) = \sum_{j \in TECH} F_{new}(p, j) \cdot \tau_{phase}(p) \cdot (c_{inv}(y_{start}, j) + c_{inv}(y_{stop}, j)) / 2$$

$$\forall p \in PHASE | y_{start} \in P_START(p), y_{stop} \in P_STOP(p) \quad (3.10)$$

The investment during a phase ($C_{inv,phase}$) results from the multiplication of the new technologies built (F_{new}) with their annualised arithmetic averaged specific cost, Eq. (3.10). The annualised phase factor is used, see Eq. (3.8), and the specific cost during the phase is defined as the average between the investment cost for the first and last year of the period.

Global warming potential calculation

$$\mathbf{GWP}_{\text{tot,trans}} = \mathbf{GWP}_{\text{tot}}(2015) + t_{\text{phase}} \sum_{p \in \text{PHASE}} \sum_{y_{\text{start}} \in Y_{\text{START}}(p), y_{\text{stop}} \in Y_{\text{STOP}}(p)} 1/2 (\mathbf{GWP}_{\text{tot}}(y_{\text{start}}) + \mathbf{GWP}_{\text{tot}}(y_{\text{stop}})) \quad (3.11)$$

$$\mathbf{GWP}_{\text{tot,trans}} \leq gwp_{\text{lim,trans}} \quad (3.12)$$

The total global warming potential (GWP) emissions during the transition ($\mathbf{GWP}_{\text{tot,trans}}$) are equal to the sum of the total emissions per period ($\mathbf{GWP}_{\text{tot}}$), Eq. (3.11). The emissions during a phase is estimated as the arithmetic average of the representative years before and after the phase. Eq. (3.12) limits the total GWP emissions during the transition by a maximum ($gwp_{\text{lim,trans}}$).

Adaptation to the case study

$$\sum_{t \in T \setminus \{h, td\} \in T_{H_TD}} (\mathbf{F}_t(y, \text{Waste}, h, td) \cdot t_{\text{op}}(h, td)) = \text{avail}(y, \text{Waste}) \quad \forall y \in \text{YEARS} \quad (3.13)$$

Endogenous non renewable wastes are constrained to be locally consumed, Eq. (3.13).

$$\Delta_{\text{change}}(p, i) \geq \sum_{t \in T \setminus \{h, td\} \in T_{H_TD}} (\mathbf{F}_t(y_{\text{start}}, i, h, td)) \sum_{t \in T \setminus \{h, td\} \in T_{H_TD}} (\mathbf{F}_t(y_{\text{stop}}, i, h, td)) \quad \forall j \in \text{TECH}, p \in \text{PHASE}, y_{\text{start}} \in Y_{\text{START}}(p), y_{\text{stop}} \in Y_{\text{STOP}}(p) \quad (3.14)$$

$$\sum_{euc \in \text{EUT_OF_CAT}(\text{HeatLowT}), i \in \text{TECH_OF_EUT}(euc)} \Delta_{\text{change}}(p, i) \leq \text{lim}_{\text{LT,ren}} \cdot (eui(y_{\text{start}}, \text{HotWater}) + eui(y_{\text{start}}, \text{SpaceHeat})) \quad (3.15)$$

$$\sum_{euc \in \text{EUT_OF_CAT}(\text{MobPass}), i \in \text{TECH_OF_EUT}(euc)} \Delta_{\text{change}}(p, i) \leq \text{lim}_{\text{MobPass}} \cdot eui(y_{\text{start}}, \text{MobPass}) \quad (3.16)$$

$$\sum_{euc \in \text{EUT_OF_CAT}(\text{MobFreight}), i \in \text{TECH_OF_EUT}(euc)} \Delta_{\text{change}}(p, i) \leq \text{lim}_{\text{MobFreight}} \cdot eui(y_{\text{start}}, \text{MobFreight}) \quad (3.17)$$

To avoid unrealistic changes in the system, additional constraints are needed during the phases for the mobility and low temperature heat sectors. Eq. (3.14) calculates the upper limit of change (Δ_{change}) in terms of supplied demand instead of installed capacity. Based on this quantification, the amount of change per phase is limited for low temperature heat ($\text{lim}_{\text{LT,ren}}$), Eq. (3.15), passenger mobility ($\text{lim}_{\text{MobPass}}$), Eq. (3.16) and freight mobility ($\text{lim}_{\text{MobFreight}}$), Eq. (3.17). As an example, setting the maximum change of supplied heat at low temperature to 25% would limit the change in technology related to heat at low temperature to 25% during a phase. In this case, if more than 25% of the low temperature heat was supplied by a technology, it would take more than one phase to replace it by a different one.

3.2 Implementation

The implementation of the proposed formulation is similar to the one proposed in Section 2.3 of the previous chapter. The definitions of the terms (SETS, Variables and Parameters) as well as the domains of the variables, the constraints and the objective function are defined in a model file. Compared to the EnergyScope TD implementation, the pathway one has three differences: the model file and data are adapted, the addition of a model file containing the constraints to set up the starting year (2015), and the files containing the definitions - *a priori* - of the terms *AGE* and *decom_allowed*. Due to the longer computation time (hours), the solver used is a commercial one: AMPL-CPLEX. The code is available on its repository [71].

4 Case study: the Belgian energy system

Chapter overview

- Belgian energy system overview
- End-use demand and resource price trends up to 2050.
- Technology characteristics and evolution up to 2050.
- Comparison of technology data with literature (LCOE, TCO).
- Overview of selected typical days.
- Demonstration with the Belgian energy system in 2015.

This chapter is an improved and extended case study version of Limpens, Jeanmart, and Maréchal [97].

The two previous chapters presented the main methodological contributions of this thesis. The resulting models can be applied to a coherent and challenging case study to illustrate their relevancies. The case study is coherent if the geographical area has homogeneous weather conditions and if energy networks are well deployed to avoid energy congestion. The case study is challenging if it is far from being carbon-neutral, having a significant demand in all the sectors, and having a limited amount of resources.

The Belgian energy system answers all these criteria. The small country known as ‘flat’ accounts for a coast at the north sea and hills in the east-south. The weather conditions are homogeneous. The energy networks are well deployed, especially for gas and electricity. However, it is challenging country as renewable energy accounts for less than 10% in the primary energy supply in 2019 (one of the worst in Europe); it is densely populated with a strong industry; and the limited renewable resources are: solar, biomass, wind, hydro and geothermal. As a result, defossilising this case study is more challenging than defossilising most of the other European countries.

Contributions

This chapter presents the Belgian whole-energy system and its perspectives on the horizon 2015-2050. The system accounts for the whole chain from the resource to the energy services. Upstream there are the resources, their price, availability, etc... Downstream, the energy demand trends. As well as, in between, the conversion technologies, the networks, etc...

All the data collected for the work are documented in this Chapter and Appendix C. Data have been mainly collected for the period 2011-2020. As many resources and technologies implemented have a low maturity, the data are subject to significant uncertainties. Since the data have been collected, new studies - up to date - may have proposed more recent and more relevant values. To face this issue and avoid misunderstanding about the key messages, all the numerical data used are documented in details with their original source, see Appendix C.

To validate the data collected with various sources from the literature, a comparison is proposed for electricity production and vehicles. As an example, the levelised cost of electricity (LCOE) for electricity production units are compared with different sources from the literature (European commission, United States Energy Information Administration ...). In addition, the model is demonstrated on a past year: 2015 (see Section 4.4.2). The model ability to represent a real energy system is verified by comparing its results with the reality recorded by the International Energy Agency and Eurostat.

Energy systems in the future

The future energy system of Belgium will be built on the existing system and improved with future promising technologies and resources. Figure 4.1 shows the energy system implemented in the model: it includes 28 layers, 10 end-use demand types, and 101 technologies (including new technologies such as the production of electro-fuels). Figure 4.1 includes today major supply routes, such as electricity produced by nuclear power plants or passenger mobility supplied by diesel cars.

While it is simple to identify future energy resources and demands, identifying conversion technologies is more complicated. On the one hand, there is a multitude of promising technologies of low maturity, such as photoelectrochemical cell which convert in a single unit solar irradiance into hydrogen (by using the moisture from air) [98]. On the other hand, each technology refers to a range of products, e.g. photovoltaic can be mono-crystalline, multi-layer etc... Selecting the appropriate technologies as well as numerical data are the major added value of the energy expert.

Built on a decade of experience at EPFL and UCLouvain, and based on other energy models, such as EnergyPLAN[44], we selected around a hundred technologies. It is interesting to see that the technologies included in the energy system evolve over the versions. As an example, in its first published version, EnergyScope TD included two technologies related to electro-fuels [25]. In

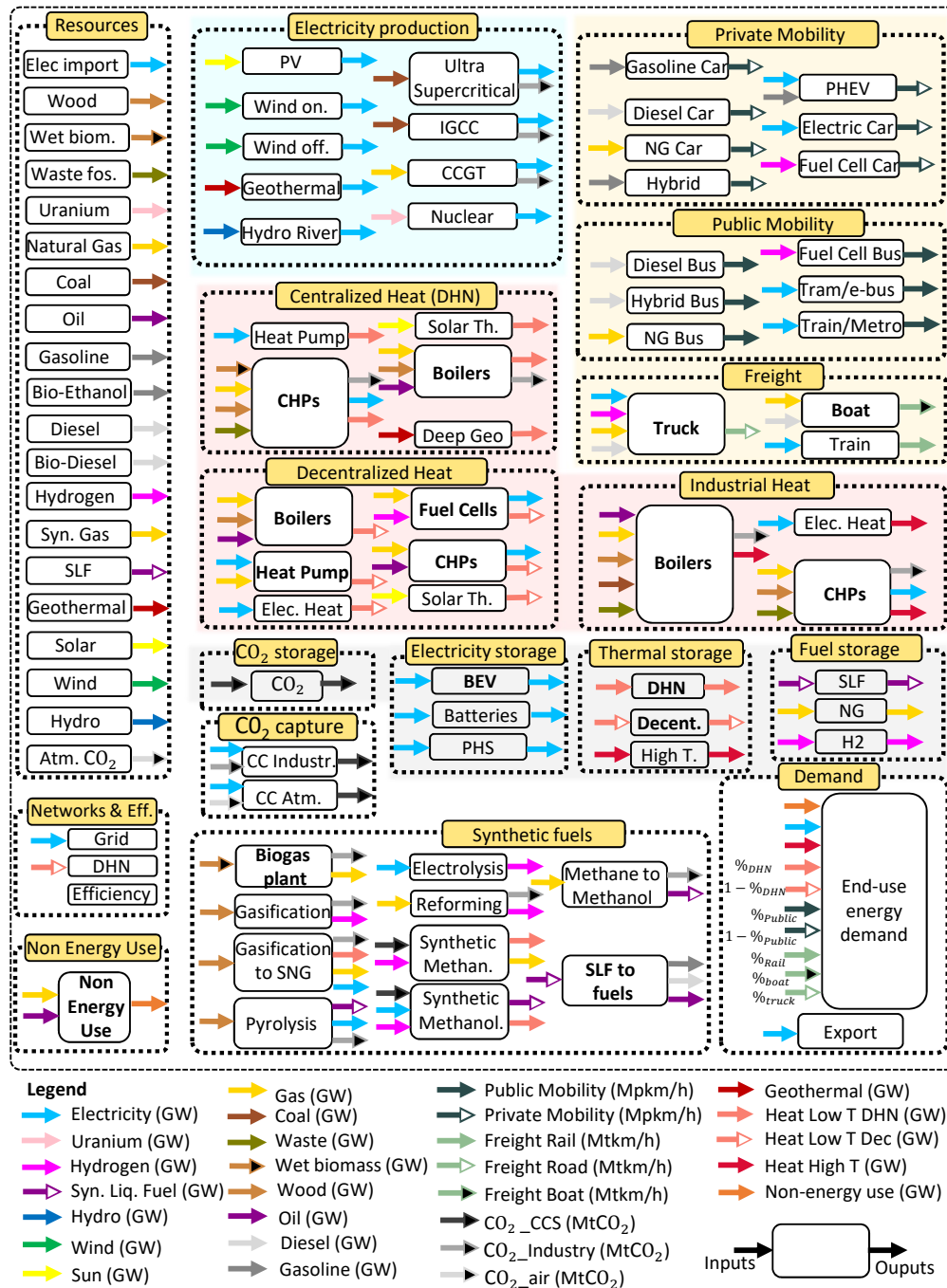


Figure 4.1 – Application of the EnergyScope TD to the Belgian energy system: overview of the resources, technologies and demands implemented. Technologies (in **bold**) represent groups of technologies with different energy inputs (e.g. Boilers include gas boilers, oil boilers ...). ‘Decent.’ represents the group of thermal storage for each decentralised heat production technology. Abbreviations: Atm. (atmospheric), battery electric vehicle (BEV), combined cycle gas turbine (CCGT), CC (carbon capture), carbon capture and storage (CCS) cogeneration of heat and power (CHP), district heating network (DHN), hydrogen (H₂), heat pump (HP), integrated gasification combined cycle (IGCC), methan. (methanation), natural gas (NG), onshore (on.), offshore (off.), plug-in hybrid electric vehicle (PHEV), pumped hydro storage (PHS), photovoltaic (PV) and synthetic liquid fuel (SLF).

the current version, three technologies have been added, mainly to upgrade hydrogen into more complex molecules. In a future version, additional technologies could be included to represent the different molecules behind the synthetic liquid fuel family.

An energy system can be represented by three boxes representing the energy stream from resources to EUD. In the following, the resources will be detailed with a focus on the endogenous Belgian potential (Section 4.1). Then, the energy demand projections will be presented in complementary to the political frameworks (Section 4.2). It will follow with technologies (Section 4.3). For this latter, the data used will be compared to literature. Finally, the model will be applied to the real Belgian energy system in 2015 (Section 4.4.2).

4.1 Resources

Resources can be regrouped in two categories: endogenous and exogenous. In the case of Belgium, endogenous resources are exclusively renewables. They account for solar, biomass, wind and hydro. The only endogenous resource which is non renewable is waste. In addition, energy can be imported from abroad (exogenous). These resources are characterised by an import price and a maximum potential. Exogenous resources account for the import of hydrocarbons, electricity or other fuels.

4.1.1 Local renewable resources

The energy transition relies on renewable energies, which makes their deployment potential a critical parameter. In 2015, 6% of the primary energy consumed in Belgium was renewable, mainly biomass, solar and wind. In the following, we summarise the potential for the different resources: in terms of available potential for biomass and waste (Table 4.2); or in terms of capacity for solar, wind, geothermal and hydro (Table 4.1). These data are put into perspective with the real data for 2015.

Wind, solar and biomass are foreseen to be the main resources. The land availability for PV is highly speculative, we propose a simple approach to estimate an order of magnitude of this limit. Assuming that it exists today 250 km² of available well oriented roof¹ [101] and that the efficiency in 2035 will be 23% [94] with an average daily total irradiation - similar to historical values - of 2820 Wh/m² in Belgium [95]. The upper limit becomes 59.2 GW of installed capacity². This limit is in line with a study performed by the Belgian transmission system operator (TSO) which proposes arbitrarily 40 GW [100]. The hydro potential is very limited and almost fully exploited. Even if geothermal heat is used for heating through DHN since 1986 at Saint Ghislain [103], research about the geothermal potential in Belgium are at their early stages. In 2015, a new project started (the Balmatt project).

¹250 km² represents almost a hundredth of Belgium's land area, which is 28635 km². The total area, accounting for water areas, of Belgium is 30528 km². From https://fr.wikipedia.org/wiki/G%C3%A9ographie_de_la_Belgique, visited the 10/08/2020.

²A similar calculation was done for solar thermal with an efficiency of 28%.

Table 4.1 – Comparison of installed capacity of renewable energies (RE) based technologies in 2015 and their potentials in the model. Abbreviations: centralised (cen.), decentralised (dec.), maximum (max.).

	Technology	2015 ^a	max. potential	Units
Electricity production	photovoltaic	3.85	≈60 ^b	[GW]
	onshore wind	1.18	10 ^c	[GW]
	offshore wind ^c	0.69	3.5 ^c	[GW]
	hydro river	0.11 ^d	0.120	[GW]
	geothermal	0	≈0 ^e	[GW]
Heat production	geothermal	≈0	≈0	[GW]
	cen. solar th.	0	≈ 70 ^b	[GW]
	dec. solar th.	0	≈ 70 ^b	[GW]

^aData from Sections 4.4.2.

^bDue to land availability, the solar potentials are limited to around 1% of total Belgian lands (250km²). This is equivalent to ≈60 GW of PV or ≈70 GW of solar thermal.

^cFrom [99]. In line with [100] which estimated 9 GW for onshore and 8 GW for offshore.

^dIn 2015, the production was 360 GWh [89] with an installed capacity of around 110 MW [101]. No important development is foreseen [100, 101].

^eA prototype (Balmatt project) started in 2019 and should produce 4-5 MW[102].

Table 4.2 – Renewable resources in 2015 and their potential.

	Resources	2015	max. potential	Units
synthetic fuels	bioethanol	0.48 ^a	0	[TWh]
	biodiesel	2.89 ^a	0	[TWh]
	SNG	0	0	[TWh]
	H2	0	0	[TWh]
Biomass	woody ^b	13.9	23.4	[TWh]
	wet ^b	11.6 ^c	38.9	[TWh]
Waste (non RE)^b		7.87	17.8	[TWh]

^aBioethanol also accounts for other bio-fuels except biodiesel. In 2015, 0.21 TWh of bioethanol have been imported, the rest of the biofuels have been produced locally from crops [2]. In the model, the crops available to produce sustainable biomass are accounted for, and can produce wet or woody biomass.

^b Endogenous potential. See Appendix C.1.

^cBelgium production of bioethanol, biomethanol, biogas and biodiesel is accounted for as wet biomass.

Nowadays, the installation produces 1.5 MW of electricity (in 2019). The project is expected to scale up to 5 MW of electricity [102]. However, there is no large facility yet and the potential is not accurately estimated. A study performed by the Vlaamse Instelling voor Technologisch Onderzoek (VITO) evaluates the potential in Flanders to 3.1 GWe and they extend it to 4 GWe for the whole Belgian potential [101]. However, because of a lack of reliable sources about geothermal potential, we consider the potential as null in the reference scenario.

The wind potential is estimated to 10 GW onshore and 3.5 GW offshore [99]. At the time of collecting the data (2011-2020), several potentials can be collected through various sources. As an example, the study from Devogelaer et al. [101] proposes to use 9 GW and 8 GW for onshore and offshore, respectively. As another example, Dupont, Koppelaar, and Jeanmart [104] estimates the wind potential based on its energy return on invested energy, in other words, its profitability. This study concluded that Belgium has a potential between 7 660 and 24 500 MW for onshore and between 613 and 774 MW for offshore³. At the time of writing, the wind energy is in the spotlight with collapsing investment costs and a rising potential. Indeed, Europe has one of the best potential worldwide and has a leading wind power industry. As an illustration of recent improvements the following argument motivates the increase of the Belgian wind potential: taller and taller wind turbines enable the use of faster and more constant wind. As a consequence, the offshore potential might be underestimated. On the other hand, the onshore potential might be overestimated as developers see their project often blocked by citizens. In a nutshell, the wind potential allowed is relevant, but perhaps slightly underestimated. As motivated in the results, due to its limited potential, wind will remain a small contributor of the energy mix with a maximum of $\approx 10\%$. Increasing its potential will be analysed later in Section 5.4.

In the literature, waste and biomass are often merged, as it is the case in the European commission report [89]. In this thesis, a distinction is made between *biomass* and *waste*. Waste accounts for all the fossil waste, such as plastics, whereas biomass is organic and assumed renewable. Biomass is split into two categories: one that can be digested by bacteria (*wet biomass*), such as apple peel; and one that cannot (*woody biomass*), such as wood. Hence, the organic waste generated by the municipalities is accounted for in *woody or wet biomass* and not as fossil waste.

In the literature, biomass potential highly varies based on the assumptions made, such as the area available to produce biomass, or the definition of sustainable biomass. Elbersen et al. [105] summarised the potential in their work '*Atlas of EU biomass potentials*'. They applied the four criteria recommended by the European Commission to qualify a biomass as sustainable, such as the land use for biomass production, or the GHG emissions related to the biomass production. They defined for Belgium fifteen different endogenous biomass types. By regrouping them into the two

³In the study, potential are given in PetaJoules of electricity per year (58-185 PJ for onshore and 8-10 PJ for offshore) for energy return on investment of 5 and 12 (see Table 13 of [104]). To convert energy into power capacity, capacity factors of 24% and 41% for onshore and offshore, were assumed respectively.

following categories, we estimated a potential of 23.4 TWh/y for woody biomass and 38.9 TWh/y for wet biomass (see Appendix C.1 for details).

4.1.2 Imported resources

As illustrated in Figure 4.1, various fossil and renewable resources can be imported, such as gasoline, diesel, uranium... or bio-diesel, hydrogen, etc. The only certainty for those who forecast future fuel prices is that they will be wrong. Indeed, as history has taught us, fuel prices are a result of a market balance where a multitude of actors are interacting. In addition, several unpredictable events can happen, such as the ongoing COVID-19 crisis. As illustrated in the thesis of Moret [46], fossil fuel prices forecasts have been overestimated by a factor of 2.95 in 2005 to 3.32 in 1995. According to Harari's classification of chaos [106], predicting fuel prices can be assimilated to a second order chaos, where the forecast interact with the future solution. However, fossil fuel prices over the next decades are needed to estimate the transition path. Based on a communication of the European Commission [107], the Joint Research Center (JRC) estimated the price trends for oil, gas and coal [108] over the period 2010 until 2050. Coal remains the cheapest fuel and has a price increase of +48%, similar to oil (+50%). Gas, instead, has a higher price increase (+84%) due to its higher market demand. In addition to fossil fuels, uranium has a constant price of 3.8€₂₀₁₅/MWh_{uranium} (details in Appendix C.1). Fossil fuels prices are summarised in Table 4.3.

Table 4.3 – Fuel prices (€₂₀₁₅/MWh) in years 2015 and 2050 for different resources. Except for biomass, all resources are imported. Upper part of the Table shows fossil resources and their equivalent renewable substitutes. Lower part of the Table shows the remaining resources. The prices are assumed to change linearly during the period 2015-2050. Abbreviations: light fuel oil (LFO), natural gas (NG), synthetic liquid fuel (SLF) and synthetic natural gas (SNG).

Year	Non-renewable			Renewable	
	2015	2050		2015	2050
Gasoline	59	94	Bio-gasoline	260	200
Diesel	57	91	Bio-diesel	280	210
LFO	43	69	SLF	240	190
NG	30	53	SNG	220	180
Coal	15	18	Woody biomass	29	36
Waste	20	25	Wet biomass	5	6
Uranium	4	4	Hydrogen (H ₂)	200	160

Renewable fuels are good candidate to substitute their equivalent fossil fuels. These fuels can be obtained from two different feedstocks: biomass and electricity. Today, most of the renewable fuels are *bio-fuels*, obtained from converting biomass. Lignocellulosic biomass, called here *woody biomass*, can be converted into hydrogen, methane or synthetic liquid fuel through different processes, such as gasification or pyrolysis. Digestible biomass, called here *wet biomass*, can be transformed into

syngas, later upgraded to biogas. The other path to produce renewable fuels is based on electricity and produce fuels called *electro-fuels*. Excesses of electricity can be converted into hydrogen through electrolyzers. This molecule can be latter upgraded to methane or synthetic liquid fuel (if captured CO₂ available).

In this version of the model, several technologies have been implemented to produce bio-fuels and electro-fuels (details in Appendix C.3.5). In addition, renewable fuels can be imported from abroad. Brynolf et al. [109] estimate a range for the production cost for some electro-fuels based on hydrogen electrolysis: methane, methanol, Di-Methyl Ether (DME), gasoline and diesel. Hereafter, we will assume that the price of an electro-fuel is equal to its production cost. In addition, imported bio-fuels are assumed to have the same price as their equivalent electro-fuel. For the sake of simplicity, we will call these fuels renewable fuels in the following without making the distinction between *electro* and *bio* fuels. Table 4.3 also summarises the prices for renewable fuels.

The last energy which can be imported from abroad is electricity. Similarly to other imports, it is characterised by, for each representative year, an averaged annual import price (c_{op}) and averaged annual specific emissions (gwp_{op}). In addition, the import of electricity is limited by a net transfer capacity ($elec_{import,max}$) (as previously introduced in Section 2.2.4). The price is expected to increase by 85%, starting at 56.8€₂₀₁₅/MWh in 2015 and increasing up to 104.9€₂₀₁₅/MWh in 2050. The specific emissions are forced to reach 0 at the horizon 2050 to reach a carbon-neutral Europe. Thus, we assume a linear reduction of electricity imported emissions, starting at 481.2kgCO₂-eq/MWh in 2015 (European electricity mix) and dropping down to 0 in 2050.

4.1.3 Accounting of the emissions

There are different methods to account for the greenhouse gas (GHG) emissions related to resources. A method can account for direct emissions, usually the ones emitted by combustion; or also indirect emissions based on the life cycle, such as the ones emitted when extracting and transporting the resource. These methods can drive to drastically different results. As an illustration, water used in hydro dams doesn't produce direct GHG emissions. However, taking into account the life-cycle GHG, these emissions are estimated between 1 and 2 200 kgCO₂ equivalent per MWh of electricity produced [110, 111], putting hydro from the cleanest to the most polluting resource⁴.

Three different methods to account for GHG are proposed: (i) accounting for combustion CO₂ emissions (based on Quaschnig [112]); (ii) accounting for the impact associated with production, transport, and combustion (based on Intergovernmental Panel on Climate Change (IPCC) 2013 method GWP100a); (iii) accounting for the previous one (ii) plus the construction emissions related

⁴The wide range is mainly explained by the use of concrete during the construction of the dam. For some cases, a little dam can offer a significant amount of hydro energy to harvest, where, in other cases, massive dams are built not for electricity production but, as an example, to make a water reservoir for land irrigation or drinkable water; and the power output is very low.

to the conversion technologies. In this work, the emissions related to a technology are implemented and is assumed proportional to the technology size (gwp_{constr}). While official agencies, such as IEA and European commission usually use the direct emissions (i), in this work the overall emissions (ii) are accounted for. The differences between direct and indirect emissions are illustrated in Table 4.4 for some resources.

Table 4.4 – The GHG emissions for different fuels and metrics. The emissions are given for the impact of the resources **Combustion** only or for the **Overall** impact of the production, transport and combustion of the resources. Biomass is the only resources where combustion emits more than overall; indeed biomass is assumed sustainable.

Resources	Combustion [kgCO ₂ -eq./MWh _{fuel}]	Overall
Gasoline / Bio-Gasoline	250 ^a	345 ^b
Diesel / Bio-Diesel	270 ^a	315 ^b
Light fuel oil / synthetic liquid fuel	280 ^a	311 ^b
NG / synthetic NG	200 ^a	267 ^b
Waste ^c	150	150
Uranium	0	3.9 ^d
Coal ^e	340 ^a	401 ^d
Biomass ^f	390	11.8

^a Based on Quaschnig [112]

^b Based on GWP100a - IPCC2013 [46].

^c GWP impact related to the treatment of municipal solid waste (MSW) in an incineration plant, including auxiliary emissions due to the operation of the plant but not including its construction. This is not consistent with the other data presented in the table, however the incineration plant is the only technology treating municipal solid waste (MSW) therefore associating the auxiliary emissions to the resource does not affect the results. Emissions related to production and transport of MSW are not accounted for. Data from [46].

^d From [113].

^e Assimilated to hard coal.

^f No difference is made between woody and wet biomass.

For fossil fuels, the emissions are driven by the combustion, and indirect emissions can increase up to 38% the total emissions. For uranium, emissions are two order of magnitude below the fossil fuels ones. For renewable resources, only biomass has been listed. Surprisingly its direct emissions are the highest one. Indeed, biomass contains less energy for more carbon compare to coal. However, the ranking changes for biomass when the life cycle GHG is taken. In this work, only sustainable biomass is accounted for. Hence, the carbon balance of biomass combustion is zero, as the CO₂ emitted during combustion is absorbed during the growth of the biomass.

In the next decades, the indirect emissions may vary, as the economy will defossilise. Thus, these emissions related to transporting the resources might be reduced, as more efficient technologies can be used. Nonetheless, for fossil fuels, the most profitable fields are used first. Thus, it remains less profitable fields, usually implying more processes, such as the sand oil which requires much

more refining. For the sake of simplicity, we assume that the indirect emissions remain unchanged over the transition. Except for electricity imported, where the indirect emissions starts from the European average mix in 2015 ($482\text{kgCO}_{2\text{eq}}/\text{MWh}$) and reaches 0 in 2050.

4.2 Energy demand and political framework

4.2.1 Energy demand

The yearly end-use demand (EUD) for all sectors are calculated from the forecast carried out by the European Commission for Belgium (see Appendix 2 in report [89]). The calculation is detailed in Appendix C. Figure 4.2 shows the future EUD trends from 2015 until 2050. Both mobility (passenger and freight) demands increase proportionally to the population. The electricity and low temperature heat increase similarly with a lower gradient. This difference comes from the implementation efficiency measures, which reduce the EUD for the same energy service. As an example of measures, the insulation of a building: the space heating demand (EUD) is reduced while the energy service (a comfortable temperature) is the same. As another example of measure, replacing the lighting with more recent technologies reduces the electricity consumption for the same illumination. There is a difference between an efficient technology and efficiency measures. We deem a technology ‘efficient’ if it consumes less primary energy for a similar or improved service than a traditional technology, such as a CCGT plant which consumes less resource for electricity production than a traditional coal power plant, or a HP which consumes less primary energy than a resistor to supply the same amount of low temperature heat. Whereas a measure is qualified as ‘efficient’ if it reduces the EUD for a similar energy service. These measures and consequently the yearly EUD are imposed *a priori*⁵. High temperature demand decreases, this reflects the impact of efficiency measures.

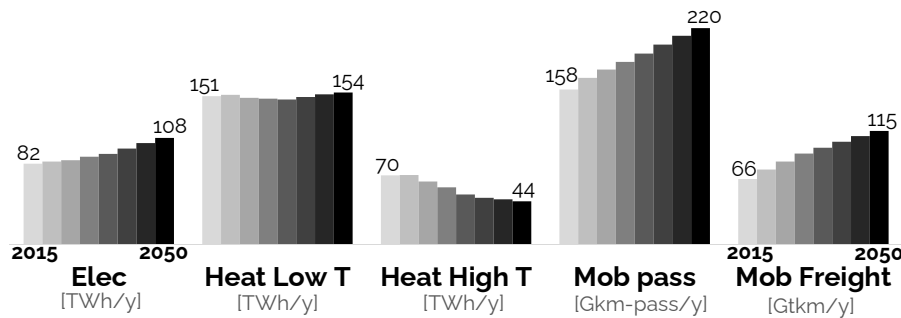


Figure 4.2 – End-use demand for the representative years.

An additional demand has been analysed in a previous work [97]: the non-energy demand. In the case of Belgium, this demand is non negligible. In 2015, it represented around 98 TWh/y, which was a sixth of the Belgian primary energy demand! The non-energy demand encompasses the energy

⁵The efficiency measure costs are implemented by Eq. 2.37 and is explained in Appendix C.3.6.

used by industries to produce goods such as petrochemical industries which convert hydrocarbons into plastic products. In [97], it is recommended that: “*the solution to defossilising the petrochemical industries is to shift from fossil fuels to synthetic fuels and biomass. As the renewable potential in Belgium is limited, the resources required to synthesise must be imported (as it is today) or the petrochemical industry must be delocalised.*”. As a limitation of this work, the non-energy sector is not accounted for.

4.2.2 Political framework

In its way to carbon-neutral society, Belgian will comply with the European green deal where European societies will be ‘*no net emitters of greenhouse gases in 2050*’ [17]. Therefore, the CO₂ emissions should decrease continuously to reach almost zero in 2050. In that year, only the emissions from waste resource will be allowed. In other words, Belgium will phase out fossil fuels, except wastes which are assumed as fossils. Coal is still used in Belgium for industrial processes, such as in blast furnace to generate high temperature heat. Thus, the coal available during the representative years is limited to the quantity used in 2015 (≈ 33 TWh/y).

Nowadays, half of the electricity production relies on nuclear. The power plants at Doel and Tihange have been built between 1975 and 1985 and are reaching their expected lifetime. Belgium nuclear plants are set to be phased out from 2022 to 2025. In 2025, only 2 GW remains available for electricity production (out of the 5.9 GW initially available in 2015).

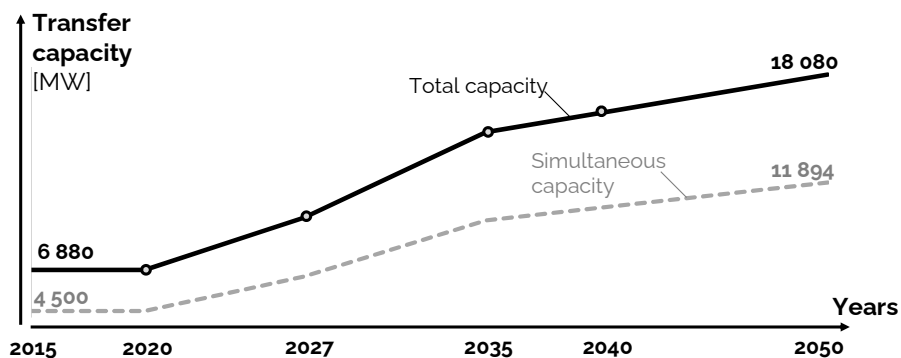


Figure 4.3 – Total and available transfer capacities from neighbouring countries.

The European Network of Transmission System Operators for Electricity (ENTSOE) summarised the different interconnections projects in their Ten-Year Network Development Plan (TYNDP) [114]. Belgian interconnections are estimated to be 6 880 MW in 2020. This capacity increases - if all projects are commissioned - up to 14 780 MW in 2035 and 15 880 MW in 2040 (see Appendix C.3.6 for details and sources). However, the Belgian TSO estimates that the full capacity cannot be used at the same time. This reflects a lack of generation capacity abroad due to simultaneous needs in two or more countries. It results in a simultaneous import capacity around 6 500 MW over the 9 880 MW

installed in 2025 [100]. This ratio is extended to the other years. Figure 4.3 summarises both total and simultaneous transfer capacities based on the previous data. Data for missing years are linearly interpolated (or extrapolated) from the curve. The capacity available in 2015 is assumed equal to the one in year 2020.

Historically, Belgium has imported 10% of its electricity from abroad⁶. In order to limit Belgium electrical dependence from neighbouring countries, the yearly electricity imported is limited to 30% of the yearly electricity end use demand. Which implies a limit on the yearly electricity import between 24.6 and 32.4 TWh/y in 2015 and 2050, respectively.

4.3 Technologies

Over the years of the transition, the technology maturities will change. Some promising technologies are expected to have an increasing efficiency and/or a decreasing cost. Other technologies are expected to become more expensive, such as diesel cars which will require more and more complex - thus expensive - filters to comply with future environmental legislations. The reference year for the technologies was set to 2035 and each numerical value used is enumerated and documented in Appendix C. Year 2035 was chosen as it is half-way between today (2020) and the end of the transition (2050). In addition, data were already collected for that year [97].

In the following, the first focus is on changes in the cost and efficiency of technologies (Section 4.3.1). Then, to assess the validity of the data, a comparison is performed in terms of levelised cost of electricity and total cost of ownership for electricity producers and mobility, respectively (Sections 4.3.2 and 4.3.3).

4.3.1 Technology improvements

To adapt these data to the different years of the transition, we used the database of the Danish energy agency. More specifically the following three reports: ‘*Technology Data for Energy Plants for Electricity and District heating generation*’ [94], ‘*Technology data for Energy storage*’ [115] and ‘*Technology Data for Renewable Fuels*’ [116]. In their well documented work, they estimate technology characteristics for the different years of the transition. In our work, only four technical characteristics will vary over the transition: investment cost (c_{inv}), maintenance cost (c_{maint}), efficiency (f) and yearly capacity factors⁷.

⁶During the period 2005-2019, Belgium was net importer most of the time (13 years over 15) with imports from 0.55 up to 21 TWh per year. Data from <https://www.febeg.be/fr/statistiques-electricite>

⁷In other words, two parameters related to the technologies are not updated during the transition. These are: specific emissions of construction (gwp_{constr}) and lifetime. In this code version, we focus on resources related emissions, and thus (gwp_{constr}) are not directly used. For the sake of simplicity, the lifetime is assumed constant to define the SET AGE and parameter $decom_{allowed}$.

Most of the data can be found directly in the cited sources, such as the price of onshore wind turbines. However, only a few years are given. Thus, the data are linearly interpolated between them. For the missing data, we made our own estimate based on a similar technology (see Appendix C.5). All the data used and their trends over the years are based on many sources and have sometimes been adapted. This motivates the work in Appendix C, where all the data used are summarised with numerical values, sources and - if adapted - the methodology to do it.

The following paragraphs just give an overview of the cost and efficiency trends for the different technologies. Some relevant examples are extracted.

Cost improvements

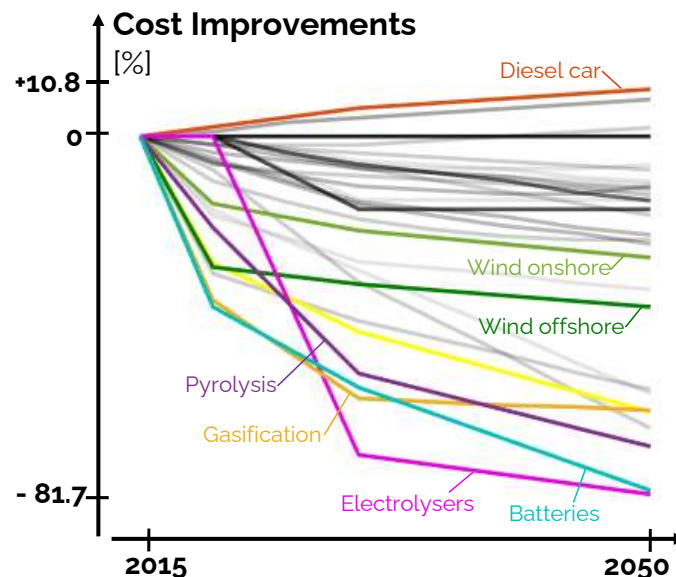


Figure 4.4 – Relative cost improvements compare to reference year (2015). Change is expressed relatively to year 2015.

Figure 4.4 illustrates the relative cost change for different technologies. All technologies are expected to have a decreasing cost, except for some private cars where the production costs will increase. Indeed, the future of the automobile is constrained by environmental legislations which oblige future generations of cars to be less polluting. Moreover, car production is today one of the strongest industries, with a very high volume and industrial automation. As an illustration, car industry accounts for one job out of fifteen in Europe⁸ and is well established since decades. As a result, there is not much room for cost reduction through economies of scale. At contrary, several technologies are expected to have a significant cost reduction, down to 81.7% less than the actual cost in 2015. Batteries and electrolysers take the biggest drop as major technology improvements are expected.

⁸Taking into account indirect jobs, source: <https://www.acea.be/>.

Cost are given relatively, thus a 80% decrease means either that cost in 2050 is low, or cost in 2015 is high; or more likely a mix of both. As an example, Batteries start at 821€₂₀₁₅/kWh in 2015 and drops down to 156€₂₀₁₅/kWh in 2050. These costs are coherent with the literature reviewed achieved by Li et al. [117], where various literature sources gave a cost between 130-270 €₂₀₁₅. The following conversion rate has been taken: 1 €₂₀₁₅ = 1.107 US\$₂₀₁₄, in 2050. The exhaustive numerical values of the cost evolution for the different technologies are given in Appendix C.5.

Efficiency improvements

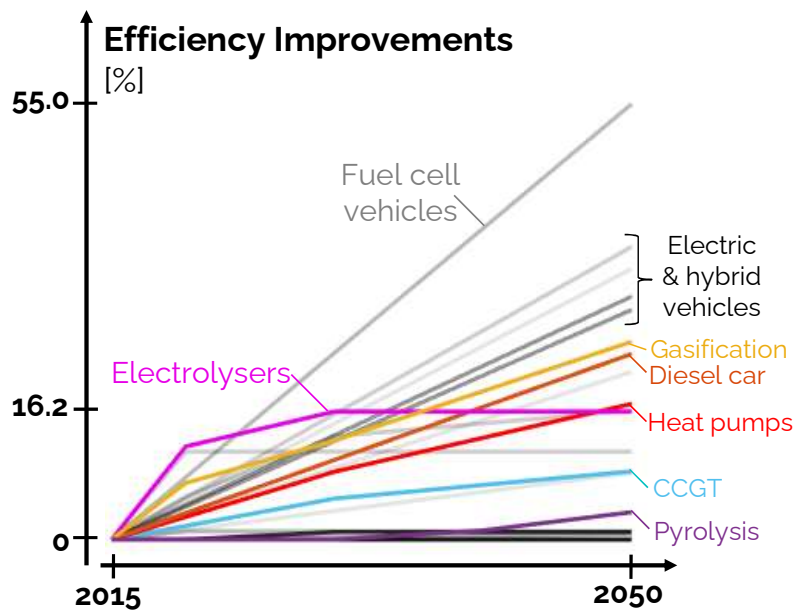


Figure 4.5 – Relative efficiency improvements compared to reference year (2015). Change is expressed relatively to year 2015.

Similarly to the previous figure, Figure 4.5 illustrates the relative efficiency change for the different technologies. All technologies are expected to have a better efficiency in the future. Especially fuel cell based vehicles (cars, trucks and buses) which assume a 35% consumption reduction in 2035. As an example, a fuel cell car consumes, per one hundred kilometer: 1.31 and 0.847 kg of hydrogen in 2015 and 2050, respectively⁹. Comparatively with today's cars, the Hyundai ix35 Fuel Cell car¹⁰ was announced with a specific consumption of 0.95 kg of hydrogen per one hundred kilometer. Other electric powered vehicles are expected to have significant efficiency improvements. As efficiencies in 2015 are slightly undervalued, the efficiency improvements appear significant. However, in 2050, their consumptions are still important. Gasoline and diesel car will consume, in 2050, 5.9 and 4.7 liters per hundred kilometers, respectively. The efficiency evolution of the different technologies is given in Appendix C.5.

⁹We used for the conversion: 1 kg of hydrogen equals 33.3kWh of hydrogen.

¹⁰Data from: <https://www.hyundai.com/en-us/releases/1624>, visited the 11-08-2020.

Data uncertainties

As a Danish proverb says: *‘it’s Difficult to Make Predictions, Especially About the Future’*. Only nominal values of the data are presented above. In addition, each of these values is fraught with uncertainty. To account for these uncertainties, a characterisation method has been applied for each parameter and will be explained later (see section 6.2). Through this paragraph, we illustrate - in advance - the importance of these uncertainties for some key parameters.

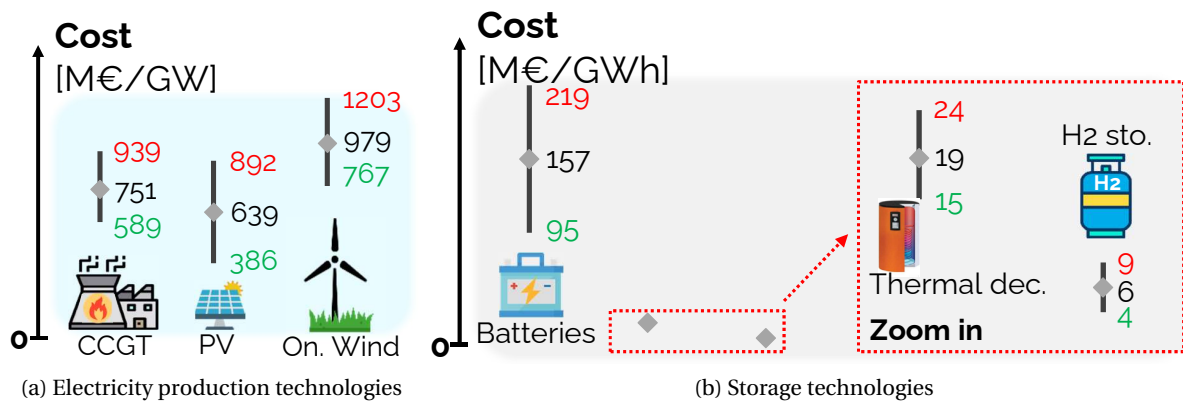


Figure 4.6 – Specific investment cost and uncertainties for some technologies, in 2050. Figure (a) represents electricity production technologies and Figure (b) represent storage technologies. Green, black and red values represent the min, nominal and max values, respectively. A zoom in is required to compare storage technologies: batteries are one order of magnitude more expensive than decentralised thermal storage and molecule storage. Abbreviations: combined cycle gas turbine (CCGT), hydrogen storage (H2 sto.), onshore wind turbines (On. Wind), photovoltaic (PV), and thermal decentralised storage (Thermal dec.).

Figure 4.6 illustrates the uncertainty ranges of the investment cost for six technologies: three for power generation and three for energy storage. For mature technologies, such as CCGT, the investment cost can vary by 47%; while for newer technologies, such as PV, it can vary by 79%. Figure 4.6 also shows us that the cost of storage technologies differ by orders of magnitude. Battery storage is 10 times more expensive than decentralised thermal storage, which is itself 3 times more expensive than hydrogen storage.

The impact of uncertainties is far from being negligible. This result encourages to account for uncertainties when analysing different energy scenarios. Further results presented in Chapter 6.

4.3.2 Levelised cost of electricity

The levelised cost of electricity (LCOE) is a common metric to compare different electricity production technologies. It measures the net present cost of electricity generation per type of technology over its lifetime. This metric relies on a financial assumption which accounts for a technology

lifetime (*lifetime*) and a discount rate. The levelised cost of electricity (LCOE) is defined as the ratio between a cost and the expected produced energy.

For a technology, the LCOE can be computed *a posteriori* based on the exact data. However, it is generally estimated *a priori* to assess the profitability of an investment without accounting for the system integration costs; this is the case of our LCOE estimation. In this case, assumptions are made on the production. The expected production is calculated based on the lifetime (*lifetime*) and the expected capacity factor ($c_{p,expected}$), which is different for each production unit: Nuclear (85%), coal (70%) and geothermal (85%) are expected to be used in base load, whereas CCGT is used less often (50%) and non-dispatchable renewables are constrained.

$$crf(i) = i_{rate} \cdot \tau(i) = i_{rate} \cdot \frac{(1 + i_{rate})^{lifetime(i)}}{(1 + i_{rate})^{lifetime(i)} - 1} \quad \forall i \in TECH\ OF\ EUT(Elec.) \quad (4.1)$$

$$lcoe_{capex}(i) = \frac{c_{inv}(i) \cdot crf(i)}{c_{p,expected}(i) \cdot 8760} \quad \forall i \in TECH\ OF\ EUT(Elec.) \quad (4.2)$$

$$lcoe_{opex}(i) = c_{op}(res) \cdot f(i, res) + \frac{c_{maint}(i)}{c_{p,expected}(i) \cdot 8760} \quad \forall i \in TECH\ OF\ EUT(Elec.), \forall res \in RES \quad (4.3)$$

The LCOE for each technology can be calculated as the sum of the CAPEX related LCOE ($lcoe_{capex}$) and the OPEX related ($lcoe_{opex}$). The CAPEX related LCOE accounts for the capital recovered, Eq. (4.2). For each technology, the capital recovered is the product of the investment cost (c_{inv}) and the capital recovery factor (crf). This later is defined in Eq. (4.1), it can be expressed in terms of annualisation factor τ . The operational expenditure related LCOE accounts for the operating expenses (c_{op}), and the yearly maintenance cost (c_{maint}). The operating expenses account for the purchase of the resources, it is calculated based on the resource costs (see Table 4.3) and the technology efficiency, Eq. (4.3)¹¹.

Figure 4.7 illustrates the LCOE trends for each technology. The one based on fossil fuels¹² have an LCOE between 40 to 59 €₂₀₁₅/MWh_e, in 2015. These costs are expected to slightly increase, except for CCGT where the increase is more significant. The total LCOE can be separated into a CAPEX and an OPEX component. In the case of CCGT, the OPEX term is predominant, and thus, the LCOE increases almost proportionally to the gas cost increase (see Figure 4.8). Technologies based on renewable are twice more expensive in 2015 than fossils, except for hydro and wind onshore which are already well spread and developed. In the incoming years, renewable are foreseen to be widely spread, resulting in a significant drop in investment costs. Whereas fossil technologies have an increasing LCOE, mainly due to resources price increase; renewable have their LCOE decreasing at a similar cost than fossils.

¹¹For the sake of clarity, Eq. (4.3) has been simplified, and only non zero value of f is represented. In other words, only the resource used is taken into account.

¹²Uranium is assimilated as a fossil energy in opposition to renewable, even if it does not come from fossils.

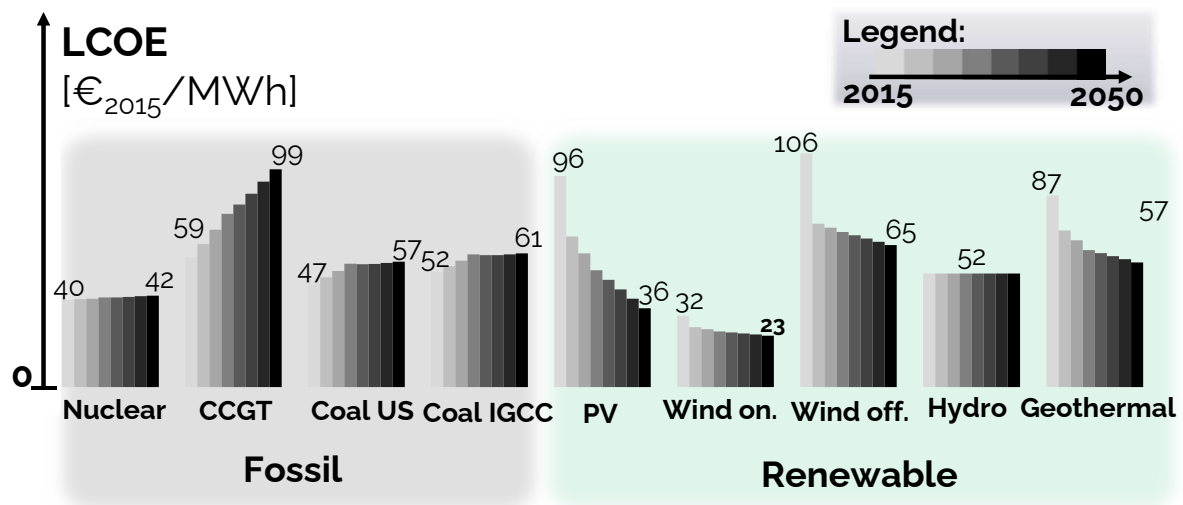


Figure 4.7 – Levelised cost of electricity (LCOE) for fossil and renewable electricity producers.

LCOE is frequently criticised for comparing apples and oranges. Indeed, some technologies are non-dispatchable and their integration in the system includes additional costs (storage, backup...). Ueckerdt et al. [118] proposes the terminology ‘*system LCOE*’, which also accounts for the technology integration costs. The study shows - for an electricity only system - that integration costs increase the technology LCOE up to 83% with 40% of wind share in the power sector; or up to 75% with 25% of PV share in the power sector.

Therefore, using the LCOE to compare different technologies is limited, however this metric can be used to compare the same technology from various sources. The latter comparison is used to verify the consistency of the data. LCOE is an indicator commonly used in the literature. We have selected three studies from different organisations and for different years. The Lazard consulting group publishes every year the LCOE world trends [119]. The Energy Information Administration (EIA) has computed the LCOE based on the data provided in the *world energy outlook* by the International Energy Agency [120]. More specific to Europe, the European Commission has estimated the LCOE for EU countries [121]. However, the assumptions used results in a large variability of the estimated LCOE. As an example, the PV LCOE is evaluated between 36-44\$₂₀₁₈ and 160-267\$₂₀₁₈ depending on the infrastructure size (utility scale or residential rooftop). In Figure 4.8, our evolution of the LCOE is compared to the previous sources.

Figure 4.8 shows typical trends for fossil: nuclear LCOE is composed of a small share of OPEX, but a large share of CAPEX; whereas CCGT has a large share of OPEX but a small share of CAPEX. Indeed, a nuclear power plant is expensive and the cost for Uranium is cheap (3.8 €₂₀₁₅/MWh_{uranium}) while a CCGT plant is cheaper but the gas price is much more expensive (30-53€₂₀₁₅/MWh_{gas}). As mentioned above, there is a discrepancy between the different sources. Especially about nuclear power plants, where considering new power plants (68-162 €₂₀₁₅/MWh) is much more expensive

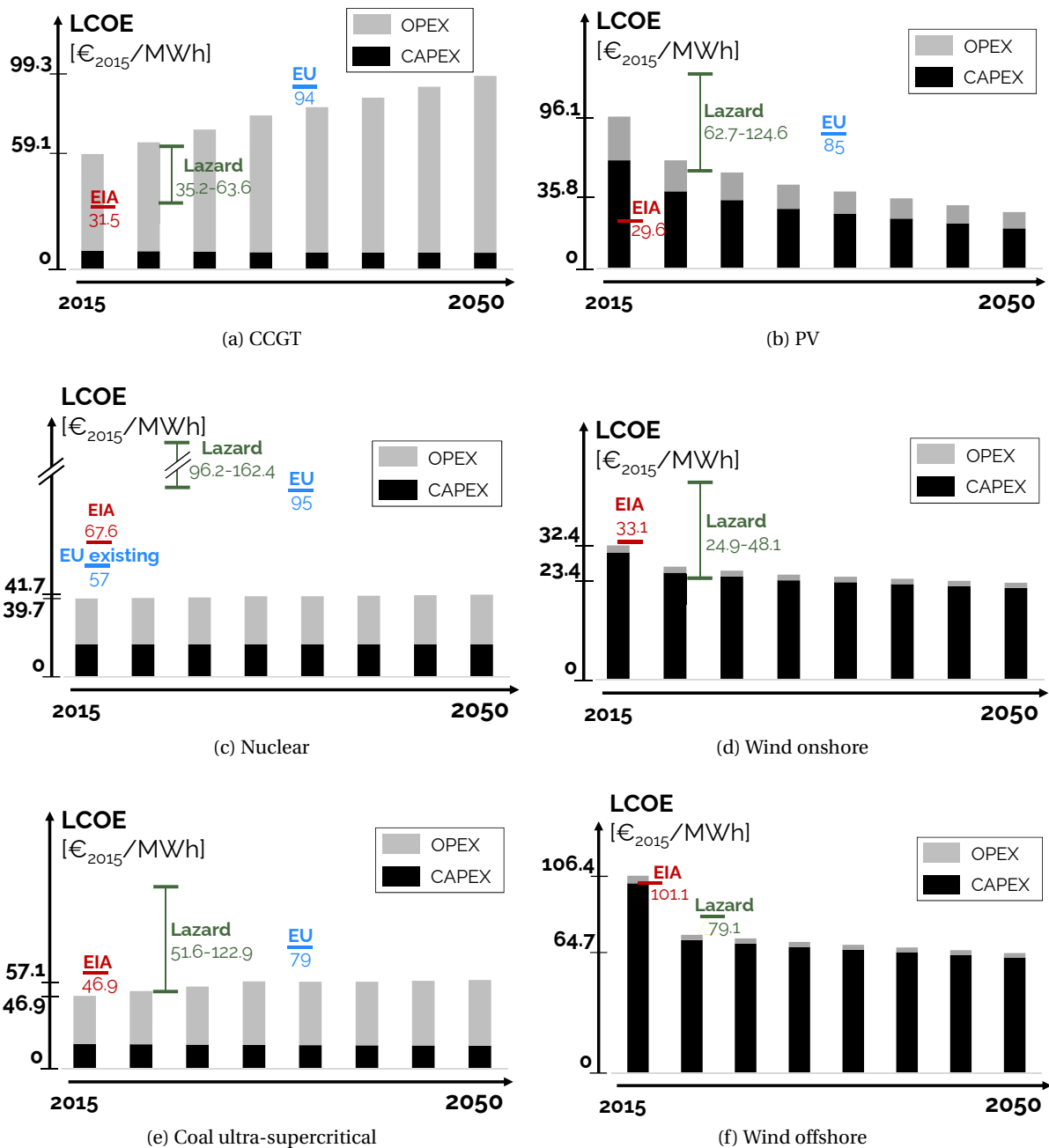


Figure 4.8 – Comparison of the Levelised cost of electricity (LCOE) with the literature [119–121]. Left column gathers fossil based technologies, whereas right column gathers renewable based technologies.

than extending existing ones (57 €₂₀₁₅/MWh). Nevertheless, we verify that our results fall between these references. Except for nuclear which is 17 €₂₀₁₅ below the lower bound. This difference is mainly due to a different interest used in the literature. According to Meinke-Hubeny, De Oliveira, and Duerinck [122] who based their work on the JRC EU TIMES model [108] in line with the PRIMES model [89], the discount rate is around 7.5 up to 12% depending on the technologies. In our work, the expenses are analysed from the country's point of view, thus we considered the central bank (Belgium national bank) interest rate (1.5%) for all the technologies. The link between the trends in the interest rate and the discount rate is highlighted in Appendix C.2.4. We motivate the use of a low value for the rate in order to reduce the delay in investments. If the rate is high, it has been observed that EnergyScope TD will favour short-lived technologies model and that the pathway extension will delay investments.¹³

4.3.3 Cost of mobility

In the literature, private vehicles are usually compared in terms of total cost of ownership (in €₂₀₁₅/km); which represents the purchase price of an asset plus its operating cost during its lifespan. In other words, the total cost of ownership (TCO) accounts for all the direct and indirect cost related to the car. The total cost of ownership (TCO) can be calculated a priori, based on the data collected for the vehicles.

$$tco(i) = \frac{tco_{inv}(i) + tco_{maint}(i) + tco_{op}(i)}{yearly\ distance(i)} \quad \forall euc \in \{PassMob \cup FreightMob\} | i \in TECH\ OF\ EUT(euc) \quad (4.4)$$

$$tco_{inv}(i) = veh_{cost}(i) \cdot \tau(i) \quad \forall euc \in \{PassMob \cup FreightMob\} | i \in TECH\ OF\ EUT(euc) \quad (4.5)$$

$$tco_{maint}(i) = \%_{maint}(i) \cdot veh_{cost}(i) \quad \forall euc \in \{PassMob \cup FreightMob\} | i \in TECH\ OF\ EUT(euc) \quad (4.6)$$

$$tco_{op}(i) = yearly\ distance(i) \cdot \sum_{j \in RES} fuel(i, j) \cdot c_{op}(j) \quad \forall euc \in \{PassMob \cup FreightMob\} | i \in TECH\ OF\ EUT(euc) \quad (4.7)$$

The TCO (tco) is equal to the sum of the annualised vehicle investment cost (tco_{inv}), yearly vehicle maintenance (tco_{maint}) and yearly fuel cost (tco_{op}); divided by the distance covered by the vehicle during a year, Eq. (4.4). The Annualised vehicle investment cost (tco_{inv}) is equal to the vehicle cost (veh_{cost}) multiplied with the annualised factor (τ defined in Eq. (2.2)), Eq. (4.5). The yearly

¹³Delaying investment shows the energy transition and therefore increases GHG emissions. Using a rate of 0.1% will reduce the overall emissions by 3% compared to the reference value of 1.5%, while using a rate of 5% will increase the emissions by 5%. This variation in emissions reflects the delay in installing more efficient technologies or using renewable resources.

vehicle maintenance (tco_{maint}) is equal to the product between the vehicle cost (veh_{cost}) and the maintenance share ($\%_{maint}$), Eq. (4.6). The yearly fuel cost (tco_{op}) is equal to the yearly distance multiplied with the resource cost (c_{op}) times the fuel consumption ($fuel$)¹⁴, Eq. (4.7). The fuel consumption is the energy required to do 1 km.

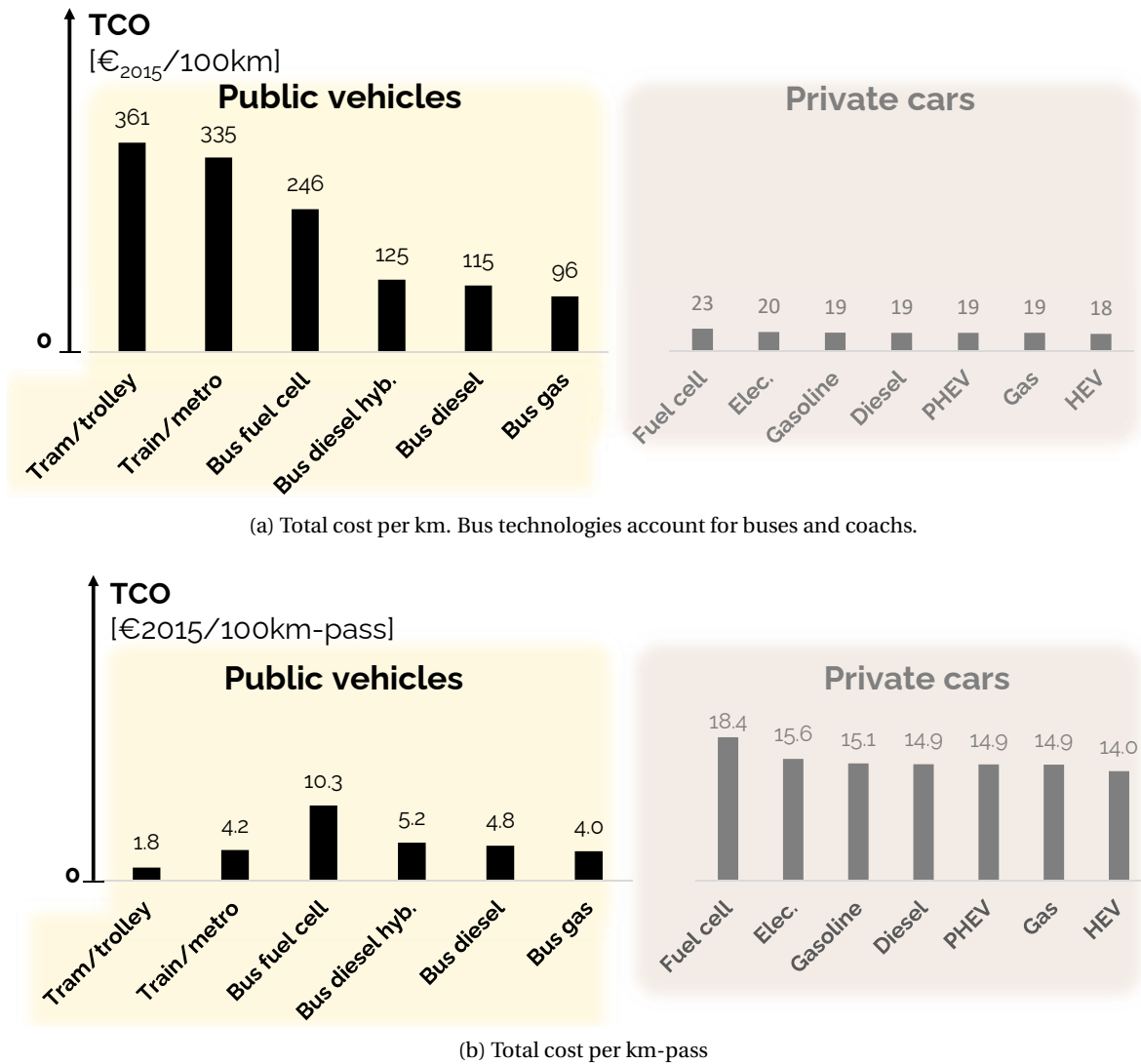


Figure 4.9 – Total cost for mobility technologies in 2015.

Figure 4.9 illustrates, for 2015, the TCO in terms of €₂₀₁₅ per hundred kilometers and €₂₀₁₅ per hundred kilometers-passenger. Both public and private technologies are represented. In terms of TCO, private mobility is around 18 to 23 (€₂₀₁₅/100km), whereas public mobility is one order of magnitude higher, between 94 and 328 (€₂₀₁₅/100km). However, this ranking is the opposite when the cost is expressed per kilometer passenger; thus, the public mobility is one order of magnitude lower (between 1.6 and 7.9 (€₂₀₁₅/100km-pass)) whereas private mobility remains more or less the

¹⁴Fuel consumption is directly extracted from the conversion efficiencies (f). Details in Appendix C.2.3.

same, between 15.5 and 26 (€₂₀₁₅/100km-pass). In fact, the model usually relies on public transports which appear cheaper and more energy efficient in all cases.

In the private mobility vehicles, fuel cell (FC) vehicles appear as the most expensive. The high TCO of fuel cell (FC) is directly explained through a high investment cost and the fuel cost¹⁵. The cheapest technology are hybrid electric vehicle (HEV) cars. Its better efficiency - energy consumption 30% lower than a conventional car - compensates the higher investment cost. Similar trends appear for buses and coaches in the public sector. Trains and trams have a higher TCO but can transport many more passengers resulting in the lowest cost per passenger kilometer¹⁶.

In the literature, Messagie et al. [123] estimate the range of TCO for private cars for the specific case of Belgium in 2012. Small city cars have the lowest TCO ranging between 18.2 to 35.6 €₂₀₁₂/km, whereas luxurious cars range around 52.0-79.2 €₂₀₁₂/km. We estimate the range between 20 to 34 which is in line with Messagie et al. [123]. In our work, the total cost of ownership is calculated based on the investment, maintenance and operating costs; while in [123], they also account for road tax, fuel tax, registration tax and insurance. As an exception, one technology is significantly more expensive in [123]: the BEV. This difference can be explained by two facts: we selected a short range distance for electric vehicle which requires a smaller battery and the BEV market landscape changed since 2012 with the production cost falling these last years [124].

To validate the set of data, two comparisons have been performed for electricity and passenger mobility sectors. The LCOE and TCO comparison show small differences, but also highlight the consistency of the set of data collected. Trends are in line with different sources from the literature [119–121, 123, 124].

4.4 Illustration

Long-term planning models cannot be validated as they model an unknown future [125, 126]. For example, they differ from the model of a physical system, where inputs can be controlled and outputs can be measured to validate and improve the model structure. Such validation is not possible for a large-scale energy system, particularly when considering future projections. However, with the availability of past and current data on the energy system under study, it is possible to verify the degree of accuracy of the model in representing the past or present state of the system. Thus, we assess whether the model can reproduce the state of the Belgian energy system in the year 2015.

The typical days (TDs) must be computed based on the different time series (Section 4.4.1). And then, the EnergyScope TD model can perform the analysis in 2015 (Section 4.4.2).

¹⁵For this example, we assumed a fuel cost of 170 €₂₀₁₅ per MWh of hydrogen. This is equivalent to buy it at around 6€ per kg at the fueling station. Today (2019), it is at 10€ per kg at the fueling station.

¹⁶Due to a lack of data on existing road and rail infrastructures and their future costs, their costs are not taken into account in the model nor in the TCO.

4.4.1 Selecting the typical days

As motivated previously (see Section 2.1), the clustering method proposed by Domínguez-Muñoz et al. [81] is applied to the case study with 12 TDs. It is the modeller's expertise to choose the time series and their weights, which will influence the choice of typical days. A rule of good practice is to include all the time series and to give an equivalent weight to each of them. Nevertheless, in the case of Belgium, there are time series which doesn't impact the system design. For example, the water flow used in run-of-river dams, or the solar thermal production. These have little influence because the installed capacity is always low (verified results). The rest of the negligible time series are those which are constant over the year, such as for high temperature heat, freight and hot water; or which have an identical profile from day to day, such as passenger mobility. As a result, the time series accounted in the Belgian case are: electricity demand, space heating demand, PV *production*¹⁷, onshore wind *production* and offshore wind *production*. In terms of weights, we impose the same importance between each of the demand profiles and those of productions combined. This arbitrary choice is motivated by the fact that the hourly demand profiles for electricity and heat are expected to have a great importance. Consequently, one third of the weights are associated with the electricity demand, one third with the heating demand, and one ninth with each of the following production profiles: PV, wind onshore and wind offshore.

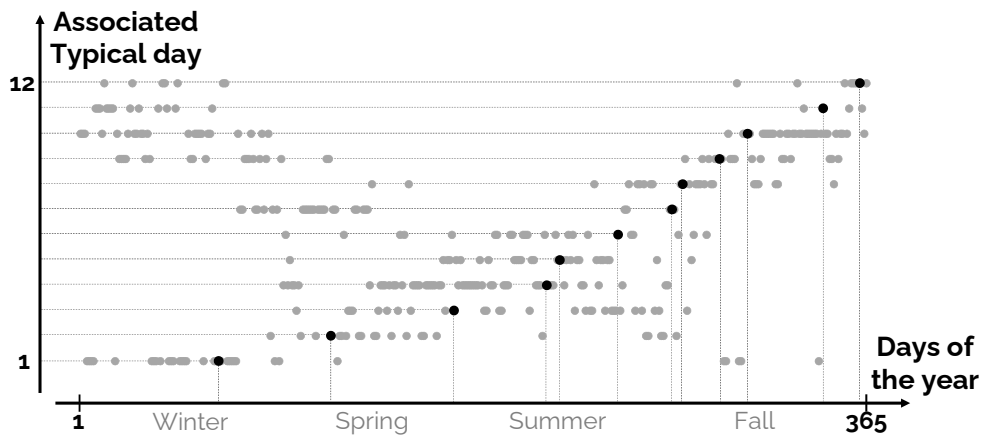


Figure 4.10 – Association of the days of the year (x-axis) to one of the twelve typical days (y-axis). Black points represent the selected typical day for each cluster (medoid). Grey points represent the day of the year.

Figure 4.10 illustrates the selected 12 typical day and their relation with the days of the year for the considered case study. It shows where the TDs are selected over the year and which days of the year are related to each TD. As an example, TD 12 is an extreme cold sunny day with few occurrences (16

¹⁷The term '*production*' is used since it refers to the Belgian real production profile (i.e. in GW) of each of these technologies, and not the irradiation or wind profiles. The difference between the two involves the geographical disparity and their implementation. For example, in the case of PV, some panels are oriented east and others west, therefore, their productions will not be the same.

days), while TD 10 is a cold windy day with many occurrences (54 days). The twelve typical days can be classified as follows:

- 3 winter days (TDs 1, 11 and 12) with high heat demand. There are nuances between them: TD-1 is a sunny day with limited wind, TD-11 is a windy day in the afternoon with a limited solar irradiance, and TD-12 is a windy cloudy day. Both TDs 11 and 12 have a very high heat demand. Finally, TD 11 has a constant electricity demand over the day.
- 3 cold intra-season days (TDs 7, 9 and 10) with a significant heat demand. TD 7 is a calm sunny day. The remaining TDs have a limited irradiance, but extreme wind speed from a calm day (TD 9) to a stormy one (TD 10).
- 3 hot intra-season days (TDs 2, 3 and 8) with limited heat demand. TD 2 is sunny with a limited wind, where TD 3 is the other way around. TD 8 has a limited irradiance and strong wind, and its electricity demand has a more constant shape.
- 3 warm summer days (TDs 4, 5 and 6). TD 6 is a windy day, while TD 5 is a sunny one. And TD 4 is a sunny day with some wind.

Using TDs filters out some of the time series information. In particular, the annual production can be miscalculated and the most constraining days can be ignored. There are several methods to compensate for this loss of information: include extreme days, add a constraint to oversize the system design, couple with another model, etc.

To ensure that the annual production matches the demand, the approach followed in this work was to scale the time series based on TDs. As a result, the sequence of TDs will give the same annual production as the real time series. Regarding the extreme days, their consideration is more complicated since there are many time series and that their correlations are also important. For example, with two time series (wind and solar), the extreme days can be the day with the least sun, the day with the least wind but also the day with the least cumulative wind and sun. To overcome this problem, we use a security factor for low temperature heat production¹⁸. For these sectors, the factor is the ratio of the real peak demand and the one implemented in the model. This approach makes it difficult to take storage into account. Indeed, should the storage level be considered as full or empty during the worst hours? To solve this problem, a finer resolution of the hourly dispatch over a longer period is needed to verify the networks adequacy. This is outside the scope of the model. Instead, we recommend coupling the EnergyScope TD model with a dispatch one (e.g. Dispa-SET [39]). The latter checks the adequacy of the networks and, if necessary, gives a feedback, through an adequacy constraint, to modify the design in EnergyScope TD. Coates and Percy have demonstrated the feasibility of this coupling [93].

In summary, each TD has its specificity and brings some information to the system. As the time series won't change in the next chapters, the following results all rely on these typical days.

¹⁸The good practice in Belgium is to have enough heating power to cover the needs of the building with a temperature of -12°C outside.

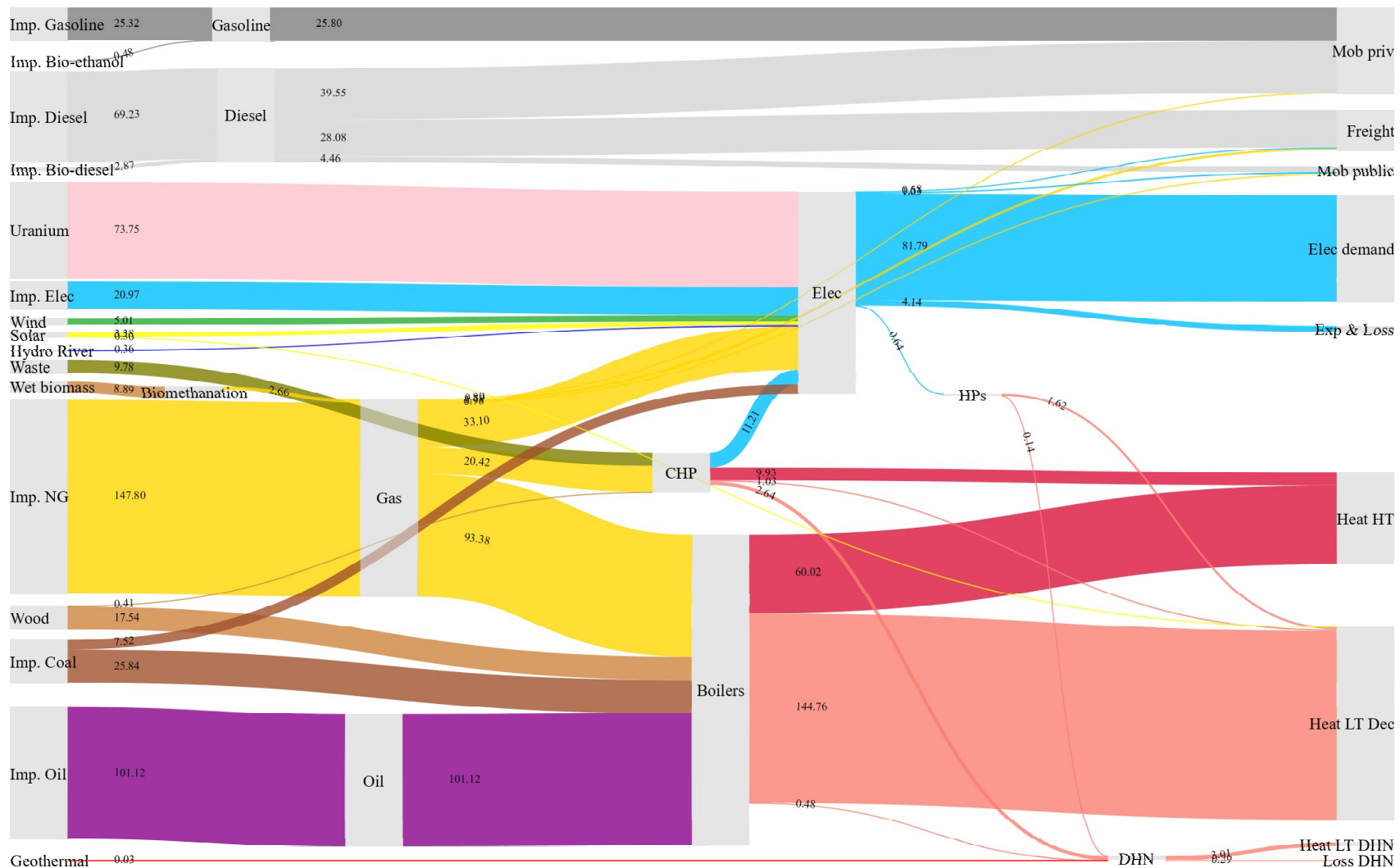


Figure 4.11 – Energy flows in a scenario representing the real Belgian energy system in 2015. The left side gathers all the resources and the right side gathers the final energy consumption. In between, the conversion technologies are aggregated by families. Abbreviations: cogeneration of heat and power (CHP), district heating network (DHN), electricity (Elec), Export (Exp) hydrogen (H₂), heat pump (HP), import (Imp) low temperature (LT), high temperature (HT), mobility (mob), natural gas (NG), private (priv), synthetic liquid fuel (SLF), synthetic natural gas (SNG), storage (sto.).

4.4.2 Application in 2015

As the Belgian energy system in 2015 is non optimal, additional constraints are added and some parameters are changed to the model to force the 2015 configuration:

1. the relative annual production share of the different technologies for each type of end-use demand are fixed, e.g. 35% of the private mobility is supplied by gasoline cars (data from the Belgian public federal service for mobility and transport, see Figure 3.7 of [127]);
2. the shares of public mobility ($\%_{\text{Public}}$), train and boat in freight ($\%_{\text{Freight}}$) and centralised heat production ($\%_{\text{DHN}}$) are those from 2015;

Section C.4 of Appendix C summarises, for the year 2015: the data used, the details about numerical values and their implementation.

The overall energy balance is illustrated in a Sankey diagram, see Figure 4.11. In 2015, the energy system is a fossil-based, with non-renewable fuels accounting for more than 93%¹⁹ of the primary energy, with low electrification of heat (6.6%) and transport (1.3%) and with marginal deployment of promising technologies such as district heating network (2%) and heat pumps ($\approx 0\%$) (data from Eurostat [2] and heat road-map Belgium [129]).

In Table 4.5, the model outputs are compared with the reported values for the year 2015, from Eurostat [2], based on the following two indicators: (i) primary energy consumption, global and per type of fuel; (ii) global GHG emissions.

In terms of energy consumption, the model offers an accurate approximation of the reported 2015 values. Little differences can be observed for different resources. The total amount of oil is overestimated (3%) due to an undervalued efficiencies of vehicles compared to the reality. The use of coal might be not totally caught as minor contributions are not accounted for in the model such as coal CHP (104 GWh/y) or residential use (858 GWh/y) [2]. The use of uranium and waste are underestimated, reflecting an efficiency in the model slightly higher than the real ones.

The total GHG emissions from fuel combustion in 2015 were between 92.5 (IEA [130]) and 97.8 MtCO₂ (Eurostat [89]). The fuel combustion emissions are accurately estimated by the model (97.95 MtCO₂). However, as explained previously, we propose to follow the IPCC2013- GWP100a metric to measure CO₂ emissions. This metric accounts for emissions related to fuel production and transportation. Thus, the Belgian emissions increase up to 128 MtCO₂/y; and the additional 30 MtCO₂/y reflects all the indirect emissions.

¹⁹According to IEA definition [88], we assume, for nuclear energy, that the primary energy equals the thermal production. This methodology is in line with Eurostat [128]. Besides fossil fuels, uranium (18.6%), waste (1.3%) and electricity imports (3.3%) are accounted for as traditional fuels.

Chapter 4. Case study: the Belgian energy system

Table 4.5 – Model verification: model outputs vs. actual 2015 values for the Belgian energy system [2]. $\Delta_{rel.}$ stands for the relative difference. Abbreviations: non-energy (N.E.) and electricity imports (Elec. Imp.).

		2015	ESTD	Δ	$\Delta_{rel.}$
Primary energy consumption TWh	Gasoline		25.32		
	Diesel		69.23		
	Oil		101.12		
	Total Oil	196.08	195.68	-0.4	-0.21%
	Total Gas	150.56	147.8	-2.76	-1.83%
	Total Coal	34.5	33.35	-1.14	-3.31%
	Uranium	78.11	73.75	-4.36	-5.58%
	Elec. Imp.	20.94	20.97	0.03	0.12%
	Solar PV	3.05	3.38	0.33	10.86%
	Solar th	0.26	0.3	0.04	14.16%
	Wind	5.56	5.01	-0.55	-9.9%
	Hydro	0.32	0.37	0.05	15.06%
	Geothermal	0.04	0.03	0	-11.78%
	Wood	15.34	17.95	2.61	17.01%
	Biogas	2.66	2.66	0	0.04%
	Biofuels	3.33	3.34	0.01	0.22%
	Total RE	30.55	33.03	2.48	8.12%
	RE.	4.39			
	non RE.	6.32			
	Total Waste	10.71	9.78	-0.94	-8.74%
	Total Energy	521.46	514.36	-7.1	-1.36%
GHG emissions [MtCO₂-eq./y]		92.5-97.8[89, 130]	96.68	1.53	1.61%

Discussion

The proposed model aims at offering a representation of the energy balance of the country and an estimation of the installed capacity. Even if the hourly operation is optimised, the model is not tailored to offer a consistent hourly dispatch. The validation results show that the model is able to capture the order of magnitude of the total capacity of the technologies and to verify its operation. Overall, the model offers an accurate picture of a national energy system for the goal of scenario analysis with high shares of intermittent renewable energies to support decision-making. In fact, at the time of writing, collecting and harmonizing the needed data to close the annual energy balance of a national energy system is still a surprisingly challenging and time-consuming effort. Especially about defining the hourly time series. If, on the one hand, there is a good availability of detailed data for the electricity sector, on the other hand, the modeling process is far more difficult for heating and mobility end-uses. This suggests that the adopted hourly resolution can be a reasonable trade-off between time and accuracy, compatible with the level of detail of available data.

5 Scenarios analysis

'A problem without a solution is a poorly stated problem'

Albert Einstein

Chapter overview

- Can Belgium reach a carbon-neutral energy system?
- How the system handle high shares of intermittent renewable energies?
- How are investment costs distributed between sectors?
- Belgium has a limited renewable potential: what are the options?

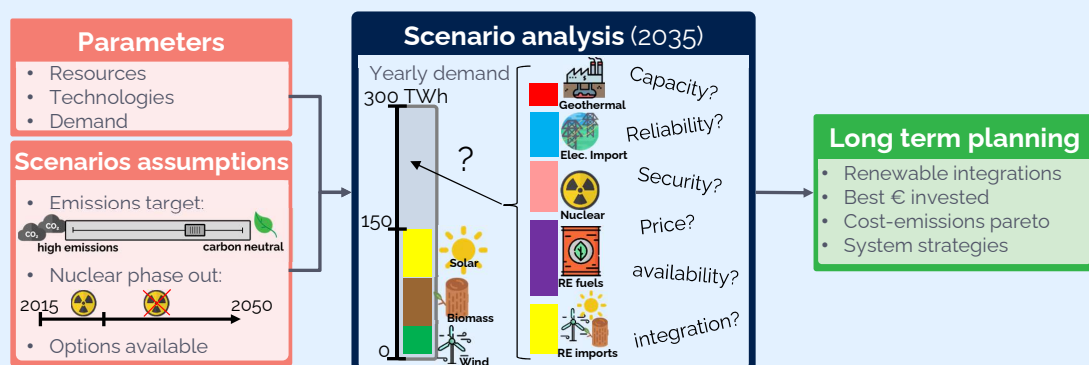


Figure 5.1 – Overview of the scenarios analysis

This chapter is an improved and extended version of previous results presented in Limpens, Jeanmart, and Maréchal [97].

The Belgian energy system is, today, far from being a carbon-neutral energy system. However, the European commission, encouraged by citizens' movements, constraints Belgian governments to reduce drastically the country greenhouse gas down to 55% and 100% in 2030 and 2050, respectively, compared to 1990. Consequently, Belgium is at the dawn of the energy transition.

As listed in the introduction, many studies exist and are related to the energy transition. In particular, the study called '*Towards 100% renewable energy in Belgium by 2050*' analysed the *whole* energy system for carbon-neutral societies. The analysis highlighted the following limitations for the models: it doesn't fulfil the criteria of Chapter 1, the Belgian version is neither open source nor open-data. In the case of the mentioned study, it was carried out in 2013, and some conclusions may be outdated. The Belgian version of the model and the data used are not shared, and thus, the findings cannot be challenged and improved.

Inspired by their study, this chapter aims to analyse different energy scenarios for the Belgian energy transition. In addition to the study, all the data used (Chapter 4) and the model (Chapter 2) are shared in openly. The model is applied to the Belgian energy system in 2035. This year appears as a good trade-off between a long-term horizon where policies can still be implemented and a horizon short enough to be representative of tomorrow society with a toolbox of technologies already known.

Contributions

This chapter aims at understanding the different possibilities to reduce the GHG of the Belgian energy system in a close future. Technical questions will be addressed, such as: can Belgium reach a carbon-neutral society? What will be the energy mix? Which are the trends to defossilise the energy system? How can Belgium integrate massively its intermittent renewable potential? What alternatives does the system have? What does it financially imply?

To do so, the Belgian energy system will be studied in four steps, one per Section. First step is to identify how far Belgium can achieve a defossilisation on its own, and when each technology becomes profitable. Second step focuses on the intermittent renewables, and the benefit of different methods to facilitate their integration. Third step analyses economically the system changes compared to 2015. As Belgium cannot reach a carbon neutrality on its own, the last step analyses different options to further reduce emissions.

The three first steps aim at understanding *how* the Belgian energy system can technically defossilise and what it will represent in terms of investments. The last step aims at identifying the most realistic scenario for the Belgian case.

5.1 Is carbon neutrality reachable in Belgium?

In this section, we study the Belgian energy system and its endogenous renewable potential. Thus, imports of renewable fuels are not allowed. Instead, the system can import fossil energy and electricity. As a reminder, the imported electricity is characterised by a net transfer capacity (9.7 GW in 2035), a price (84.3€₂₀₁₅/MWh) and associated CO₂ emissions (206 gr_{CO₂,eq.}/MWh_e) (see details in Section 4.2.2), this is tantamount to say that emissions from the European electricity sector are halved and the price has increased by 50% compared to 2015. In a nutshell, the energy system studied has similar boundary conditions to the ones in 2015 (except for biomass and imported electricity). To allow Belgian energy system to reach low emissions, the solar potential is unlimited. Indeed, one assume that solar energy can be collected everywhere. This assumption will be discussed in terms of land covered by the technology.

5.1.1 Primary energy

Figure 5.2 shows the primary energy supplied for 2015 and for different CO₂ emissions constraints in 2035. Scenarios are not related to their neighbours and must be analysed separately. One can see a transition from high emissions to low emissions; however, this is a view of the mind because the scenarios do not represent a transition path. This motivates the separation of scenarios by stacks in the following figures (bar charts).

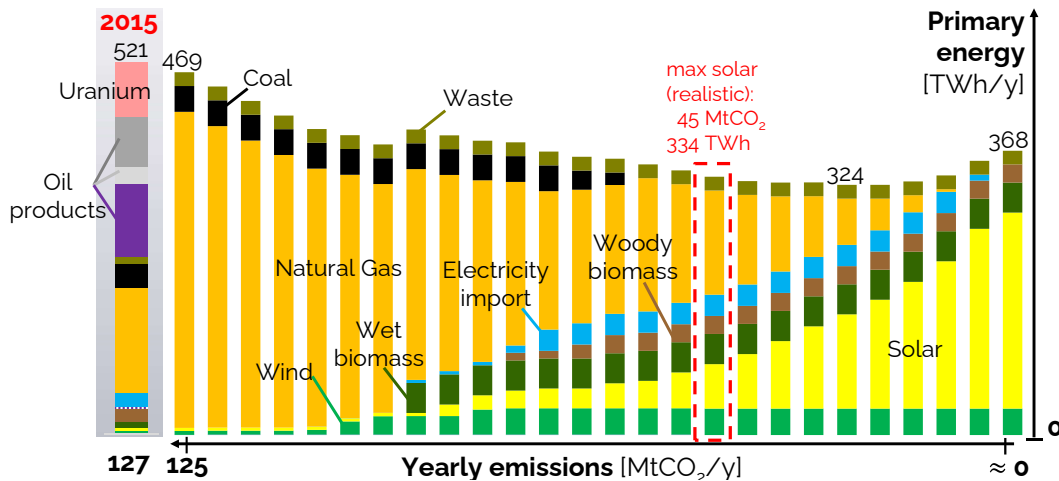


Figure 5.2 – Primary energy supply for the unlimited solar scenarios. The grey box represents the results for 2015 (presented in Section 4.4.2), the rest represents scenarios in 2035 for different yearly CO₂ emissions targets. Each bar is independent from the others. The framed case represents the result for a realistic limitation of PV (60 GW).

Focusing on the resources, the change of paradigm is clear: fossil are going to be replaced by renewable resources and electricity imports. Without limitation on CO₂ emissions, coal and gas are

the most used resources as they are the cheapest fuels. Coal has a limited availability (≈ 33 TWh, which is the amount of coal used in 2015). To reduce the system emissions, at first, more efficient technologies are used.

By shifting to heat pumps in the low-temperature heat sectors and by gas CHPs in the industrial sector; the heat can be produced at a lower cost and consume less primary energy. In parallel, technologies based on RE are deployed, first wind, then digestible-biomass (later called wet biomass), woody biomass and solar. In addition, non-RE wastes are used from the beginning and electricity imports arise at $65 \text{ MtCO}_2/\text{y}$. The use of imported electricity is highly dependent on its indirect emissions. In this study, electricity imports emit about half of the electricity production of a CCGT. Therefore, imported electricity replaces the production of CCGTs¹. Once coal is phased out ($\leq 55 \text{ MtCO}_2/\text{y}$) and all renewable potentials - except solar - are exploited, the system relies on PV to reduce its NG consumption.

The deployment of PV takes place in two stages: first, below $90 \text{ MtCO}_2/\text{y}$, a capacity around 14 GW is deployed; then, as soon as no other renewable resource is available, PV starts to be massively exploited. The first deployment of capacity is cost-competitive, as its integration requires little effort. On the contrary, the second deployment is forced due to the lack of an alternative. At this stage, decreasing emissions implies replacing dispatchable NG by intermittent PV electricity². This change strengthens two phenomena: electrification of heating and mobility sectors and curtailment of PV peaks (PV capacity reaches up to 244 GW).

Compared to 2015, the use of oil products and uranium disappears. This is the consequence of three changes. First, nuclear is no longer allowed as the country is expected to phase out its capacity in 2025. Second, the mobility mainly relies on electricity, fuel cells and NG in all scenarios. This is a consequence of high efficiencies of electricity-based technologies and to the gas price which is more than half price compared to gasoline or diesel. At low CO_2 emissions ($\leq 20 \text{ MtCO}_2/\text{y}$), biodiesel is produced from wood pyrolysis to supply hybrid diesel buses and diesel boats. Third, light fuel oil (LFO) is replaced by coal and gas for heating. Indeed, as there is a small cost difference between oil or gas-based boilers and CHP technologies, the fuel cost is more critical. As the price in the model for light fuel oil (LFO) is at least 40% more expensive than gas and coal, this fuel will be avoided.

The primary energy consumption decreases as we impose a reduction of CO_2 emissions in the system³. In the first scenario (high CO_2 emissions), the system needs 469 TWh of primary energy. This is slightly less than in 2015. This amount is reduced below 324 TWh between 25 and $20 \text{ MtCO}_2/\text{y}$ and then increases for lower CO_2 emissions. This primary energy reduction is achieved thanks to

¹As the LCOE of CCGT is lower than the cost of imported electricity, this result happens because imported electricity has lower emissions than the one produced with CCGT. If this was not the case, the system would not import much electricity as it has been observed in [97].

²Solar energy for thermal heating is also implemented but unused. The reason is explained in a later paragraph.

³An exception is made around $85 \text{ MtCO}_2/\text{y}$, where wet biomass starts to be used. Indeed due to its low conversion efficiency, to replace 1 GWh of NG, much more wet biomass is needed.

the integration of more efficient technologies.

At lower CO₂ emissions (≤ 20 MtCO₂/y), the primary energy needed increases. This can be explained by three facts related to the difficulty to integrate a large PV production (up to 60 GW in the realistic case, and even more in the cases studied in this section). First, the system relies more on storage technologies to provide flexibility. Second, a flexible resource (i.e. NG) is exclusively replaced by an intermittent one (i.e. solar), hence production peaks are hard to absorb and are partially curtailed. Third, excesses of electricity are converted into fuels, later used during energy scarcity. This conversion chain implies a lot of losses. As a consequences, extra primary energy is needed to compensate their losses.

Limited RE resources can be integrated in the heat and mobility sectors. In our work, the renewable resources for heat supply are biomass (i.e. woody and wet) and thermal solar. The latter does not appear as a promising technology for two reasons. First, it has a negative correlation with heat demand: when there is strong irradiation, there is usually a warmer ambient temperature and the heat demand is lower. Second, thermal solar needs to be backed up during lack of sun, which is normally done by fossil fuel boilers. The latter fuels are no longer available at low CO₂ emissions.

The electricity sector is the first one to reach a high penetration of RE. The other sectors cannot be defossilised completely because they do not have the necessary resources. Therefore, electrification through technologies such as trains, HPs, direct electrical heating... allows heat and mobility sectors to use renewable electricity.

To better understand the integration of the technologies, it is necessary to have a look at the deployment of technologies along the different scenarios.

5.1.2 Technologies merit order

In the following, we propose to analyse the previous results from an annualised cost perspective, and more precisely, through a Pareto frontier graph. As linear programming problems have only one objective, the total annual cost of the energy system and the CO₂ emissions can be alternatively used as objectives to minimise. Then, the two objectives can be combined using the ε -constraint method [131]. This method seeks trade-off solutions by formulating a bi-objective problem in which one of the objectives is minimised, and the other is constrained by an upper value ε , which is set parametrically (gwp_{limit} in Eq. (2.34)). As a result, the graph shows a front, which represents for each targeted CO₂ emissions, the cost of the optimal system. Hence the Pareto graph shall stop at the lowest yearly system cost. Here, we force the system to emit more CO₂ in order to get closer to the system in year 2015. Compared to the cost optimum scenario, emitting more CO₂ means consuming more fossil resources which results in an overall cost increase. These scenarios are not Pareto equilibrium.

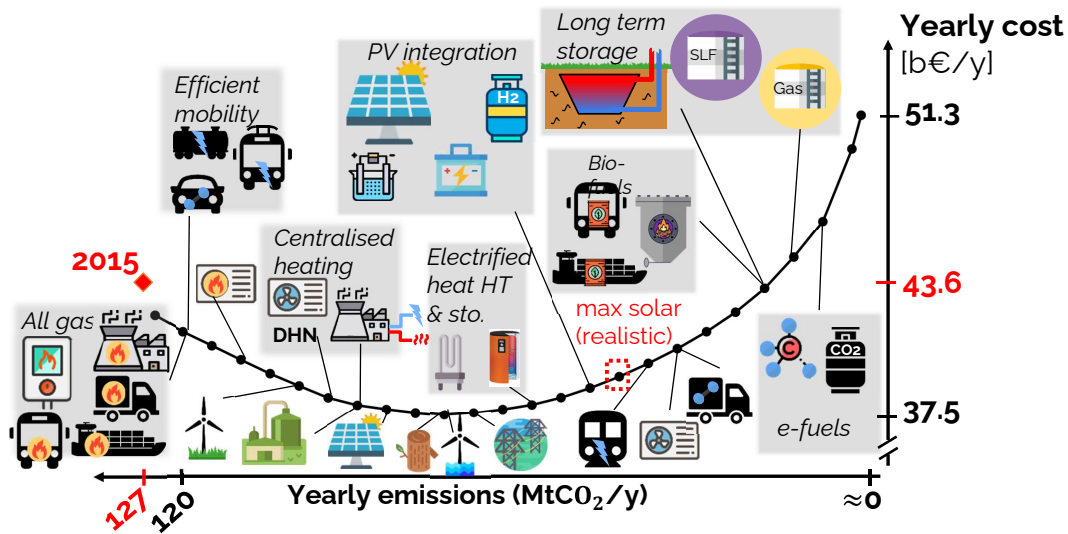


Figure 5.3 – Cost - CO₂ emissions optima and technologies implementation for the unlimited solar scenarios. Grey boxes represent group of technologies with the same characteristics. The red diamond represents the result obtained for 2015. Icons and grey boxes represent technology deployments. The framed case represent the result for a realistic limitation of PV (60 GW).

Figure 5.3 illustrates the system cost evolution during the energy transition. At first, the overall cost decreases. On the one hand, using less primary energy results in a lower cost for the resources which reduces the system OPEX. On the other hand, more efficient technologies are more capital-intensive which leads to an increase in CAPEX. The balance results in a decreasing yearly total cost down to 75 MtCO₂/y.

At first (125 MtCO₂/y), the electricity is produced by CCGTs power plants (94 TWh/y) and renewables (6.8 TWh/y). The high and low temperature heat demands are exclusively supplied by coal, gas and waste boilers. DHN is at its minimum (2%). The fuels used in mobility are NG and electricity: NG mainly for freight and public mobility, and electricity for tramways and trains. In addition, hydrogen (H₂) is produced by NG reforming and later used for private mobility.

In Figure 5.3, the reduction of emissions is split in 6 steps which can be logically grouped in 2 categories: efficiency and defossilisation. First part is a transition to more *efficient technologies* as previously explained. Between 125 and 75 MtCO₂/y included, renewables are integrated in the power production; gas boilers are replaced by gas-HPs for low-temperature and by wood and waste boilers in high-temperature application. Below 90 MtCO₂/y, onshore wind, hydro and DHN are fully deployed. In addition, NG CHPs replace coal boilers and the system achieves its optimum cost at 75 MtCO₂/y. Below, the integration of more efficient technologies increases the overall system cost. PV becomes significant (≈ 22 GW) and high temperature is electrified through resistors. This facilitates the PV integration. Electricity imports are also used to balance PV's intermittency. At this stage, thermal flexibility is used to absorb excesses of PV. At low-temperature level, HPs are

coupled with thermal storage and heat is produced during peaks (usually noon), stored and later used when electricity is lacking (usually nights). At a high-temperature level, the supply switches between direct electricity during excesses and CHPs during scarcity.

In between efficiency and defossilisation categories, the *synthetic fuel* production appears, mostly from wet biomass that is digested, cleaned and converted to synthetic natural gas (SNG). Also, pyrolysis transforms woody biomass into synthetic liquid fuels (SLFs), later converted and used for private and public mobility. Section C.3.5 of Appendix C.3.5 details synthetic fuel production technologies.

At emissions lower than 50 MtCO₂/y, PV is massively deployed and the defossilisation starts. The excesses were absorbed through power to heat (PtH) but now require also batteries, electrolyzers and hydrogen storage. These technologies are part of the *PV integration* step. At lower emissions, the amount of hydrogen produced by electrolysis becomes significant. H₂ storage is deployed to smooth H₂ production and buffer between production (during the day) and supply (day and night). At low emissions, DHN uses thermal storage for *long-term storage*. In addition, the excesses of H₂ production in summer are converted into SNG and stored to supply gas backup power plants (CCGTs and CHPs) in winter.

At almost carbon neutrality, the energy system has deployed 244 GW of PV panels, which represents roughly 1 000 km², i.e. a thirtieth of Belgium land area. This solution is unrealistic and the PV potential will be limited in the following to a more realistic potential of 59.2 GW (see Section 4.1.1). Applying this limitation to previous results will limit the reduction of emissions at 45 MtCO₂/y. Hereafter, the reference solution refers to the results presented with the realistic limit on the PV potential.

5.2 Handling high shares of intermittent renewable energies

The paradigm changes when reducing the emissions: intermittent renewables become the major primary energy contributor by substituting fossil resources. Despite their advantages, their intermittency implies major changes in the energy system. To counterbalance it, there is a need for increased flexibility of the whole system. The methods to increase system flexibility can be split into five categories: (i) imports – exports of electricity; (ii) flexibility of the production (fuel based as a backup); (iii) flexible demand through sector coupling; (iv) storage; and (v) synthetic fuels.

To assess the benefit of each option, we remove the related resources/technologies of each option: (i) electricity imports; (ii) fossil power plants (CCGT, coal ultra-supercritical (U-S), coal integrated gasification combined cycle (IGCC) and gas CHPs) are constrained to be base-load producers⁴ (similar

⁴This choice is motivated as we verified that the system can hardly rely exclusively on electricity imports and intermittent renewable productions.

to Eq. (2.23) for nuclear); (iii) technologies which bridge between electricity and another sector, this involves: resistors (industrial and decentralised), electrical heat pumps (HPs) (centralised and decentralised), electric mobility (trains, metro and trams are imposed to their levels of 2015); (iv) storage technologies; (v) technologies that can produce synthetic fuels⁵, such as electrolyzers, biomethanisation, methanation...

In the following, we focus on the range 90 to 45 MtCO₂/y. At higher emissions, trends are similar; and below 45 MtCO₂/y, no solution exists due to a lack of low emissions resources. The results are compared in term of a Pareto equilibrium in Figure 5.4.

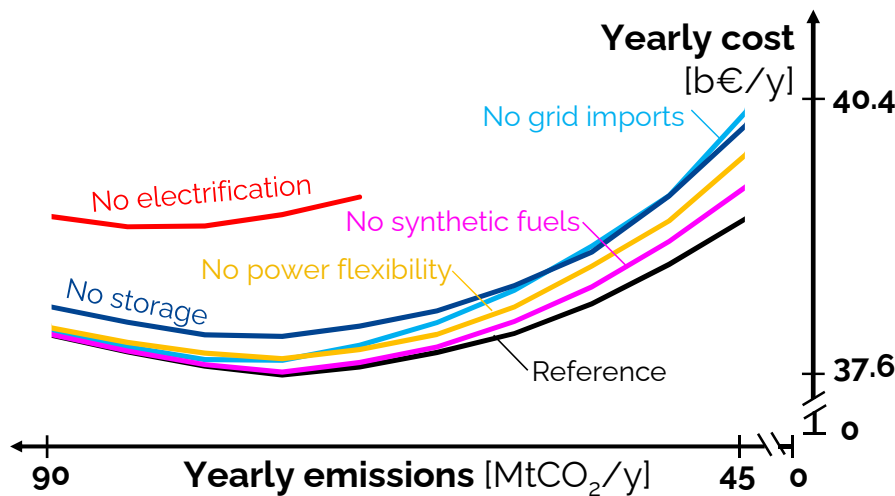


Figure 5.4 – Cost - CO₂ emissions optima for the different flexibility options.

5.2.1 The importance of electrification

Most of the options can implement the full intermittent renewable potential and reach 45 MtCO₂/y. The only exception is the scenario *no electrification* in which renewable resources for mobility and heat are limited. Figure 5.5 shows the hourly electricity balance for TD-2 (i.e. sunny warm day with limited wind) with curtailment happening at noon when there is a peak of 8.8 GW of PV. In addition to be unavoidable, electrification brings two other benefits to the system: (i) it allows the integration of efficient technologies which decrease the primary energy needed; (ii) coupled with local storage, the other sectors technologies behave as a flexible consumer which facilitates the integration of intermittent renewables. In a nutshell, electrification results in system cost reductions and is an efficient path to integrate intermittent renewables. As an example, in Figure 5.5, the DHN HPs production is driven by the electricity sector and decoupled of the heat demand. Indeed, the production peak is 3 hours before the DHN peak demand. This delay is possible thanks to the use of

⁵Methane reforming is not accounted for in these technologies. We assume that ‘*synthesis*’ involves the production of a molecule more complex than its reagents.

thermal storage.

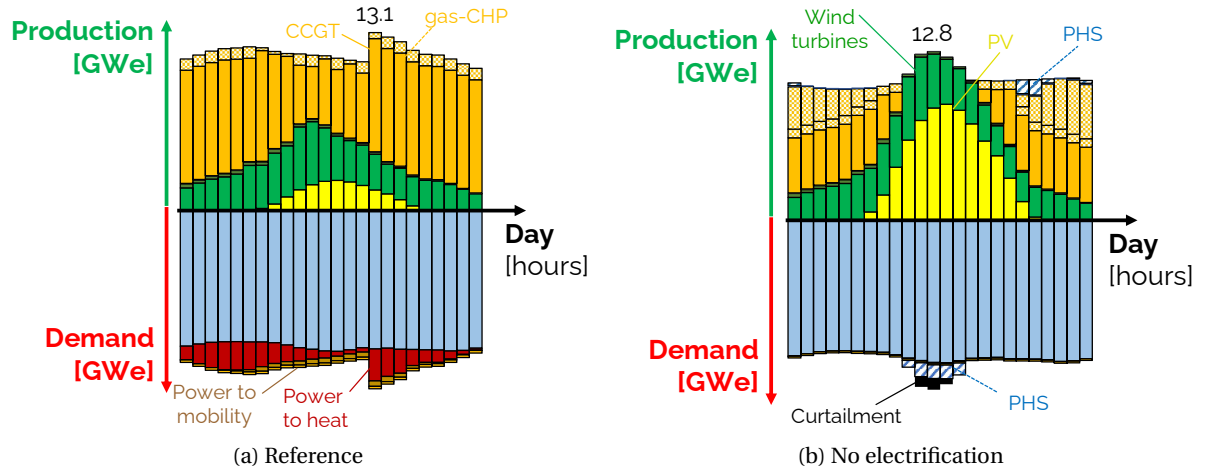


Figure 5.5 – Hourly electricity balance of a scenario with no electrification (b) compared to the reference one (a). The represented day is the typical day 2 (i.e. April 27th), an intra-season hot day.

Most of the cost difference comes from the vehicle's strategy. Without electrification, the cheapest options for passenger mobility and freight are buses and trucks. These are cheaper but have a shorter lifetime. Overall, their annualised cost are much greater than trains and trams. It results in an extra cost, which reaches 854M€₂₀₁₅ for 90 MtCO₂/y. In Figure 5.5, one can see that the electricity used for mobility peaks at 560 MW in the reference scenario.

5.2.2 The role of storage

Storage technologies allow to downsize the capacity production. Without them, heat and hydrogen production capacities, among others, are equal to the peak production/demand. Thus, without storage, the system oversizes several technologies which results in a greater cost. Once intermittent renewables start to be massively integrated (≤ 60 MtCO₂/y), peaks of electricity are too expensive to be absorbed and, thus, are curtailed. Consequently, additional capacity is installed and it results in a higher system cost. Indeed, using storage, especially low temperature thermal storage, offers a cheap solution to shift excess of production during some days to other ones. Figure 5.6 shows - for the reference case - energy stored in two different thermal storage technologies. The first one represents a seasonal storage used at a week to month scales. The second one represents a daily thermal storage used to support decentralised heat pumps. Unsurprisingly, seasonal storage is significantly larger and can contain 25 times more energy than the daily one. However, the amount of energy stored in each storage is the other way around: seasonal storage stores 16.7 TWh/y while daily one stores 27.2 TWh/y.

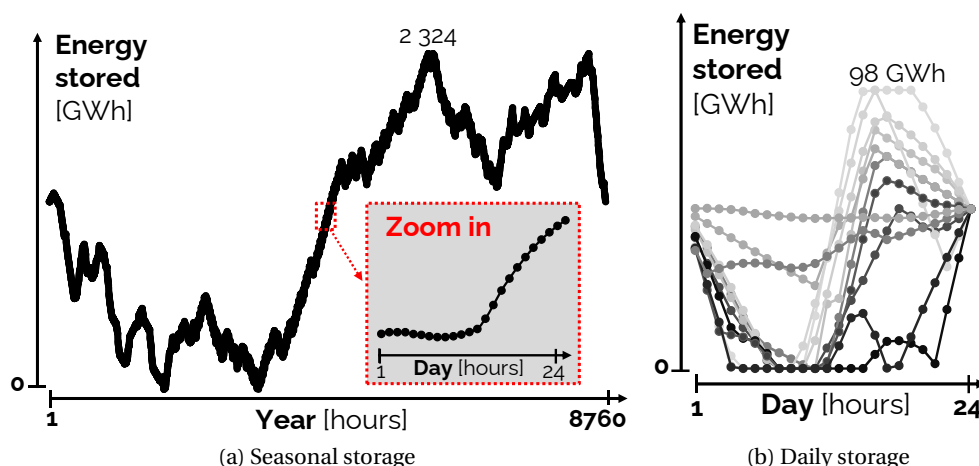


Figure 5.6 – Energy stored on two different thermal storage technologies: a seasonal (a) and a daily (b). The seasonal storage (i.e. district heating network storage) is represented over the year with a zoom in for a day. The daily storage (i.e. decentralised storage for heat pumps) is represented for the 12 different Typical days (scale of grey).

5.2.3 The role of other flexible options

The remaining options at high CO₂ emissions are similar to the reference case. The results are obvious for electricity imports and synthetic fuels, where, respectively, few electricity is imported and no synthetic fuels are produced. However, the results are more surprising without power flexibility: the electricity is produced with base load CCGTs (8 GW) and electricity import with PHS provides the flexibility.

With greater share of intermittent renewables, solutions start to diverge from the reference one for different reasons. The lack of power flexibility forces the system to over produce electricity. Thus, the absorption of intermittent excesses is achieved but at greater costs (batteries, direct electricity heating...). Without electrical imports, the strategy to balance the grid is different. On the one hand, additional technologies are required to produce electricity (PV) and to integrate it (among others): backup power plants and electrolyzers. On the other hand, imported electricity is twice more expensive than gas. It results in an increasing cost. Without synthetic fuels production technologies, the digestible biomass cannot be valorised. Thus, all the biogas normally produced is substituted by imported NG resulting in higher emissions and higher costs. Thus, without synthetic fuel production technologies, and thus without biomass conversion technologies, additional natural gas is imported which implies greater CO₂ emissions at a higher system cost.

Handling high shares of intermittent renewables is a challenge and all options are necessary for different reasons. Electrification is mandatory to provide renewable energy to other sectors and reach a low emissions society. On the electricity production side, power plant flexibility and electricity

imports compensate the intermittency of renewables. On the electricity consumption side, storage and synthetic fuels facilitate the integration of intermittent renewables, respectively buffering it or transforming it into hydrogen. Not using all the options implies an increase system cost of more than 1 b€₂₀₁₅/y, which is less than 3% of the total system cost. This little difference will be explained when analysing the cost in the following section.

5.3 Impact on the system cost

The objective of the model is to minimise the annualised system cost. As a reminder, the latter accounts for the maintenance and annualised investment cost of technologies, plus the operating costs. In this section, a focus is made on the expenses per sectors and resources. The reference scenario will be compared to the results for year 2015.

5.3.1 Cost distribution

Figure 5.7 shows the costs of the different scenarios and compares them to the costs in 2015. The costs are grouped by technologies and resources. Resources are broken down into renewable and non-renewable resources. The technologies are divided between production ones, regrouped by sectors: electricity, heat and mobility; and infrastructure. The latter accounts for storage technologies, synthetic fuel production technologies, networks (electricity and district heating) and efficiency measures to reduce energy demand (imposed by Eq. (2.37)). The mobility and heat sector is broken down by type of end-use demand. Costs related to cogeneration of heat and power are accounted for as heat production technologies.

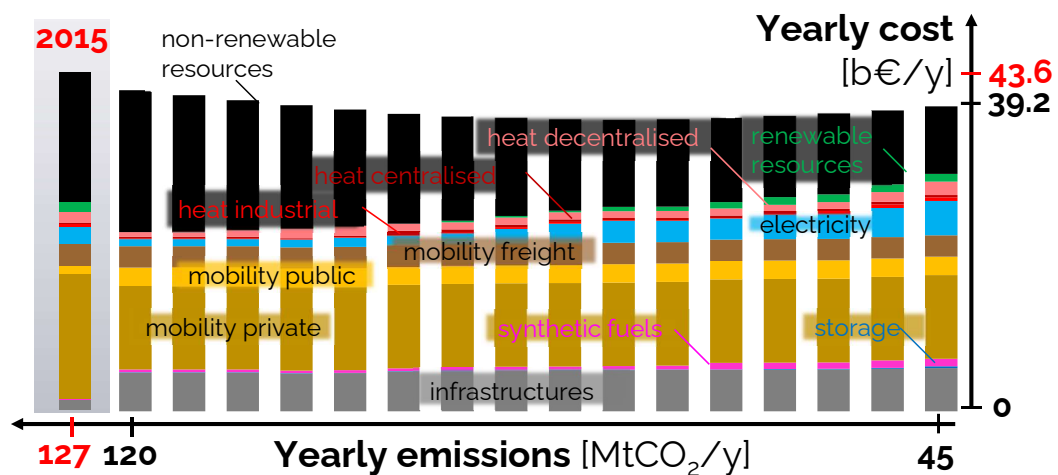


Figure 5.7 – Total annualised cost for different scenarios in 2035 compared to 2015. The costs are broken down by investments per sector, and resources. The latter is split into non-renewable and renewable ones. The latter represents the purchase of biomass and renewable fuels.

Expenses in 2015

In 2015, the cost was determined by: mobility technologies (45.8%), purchase of resources (41.0%), power generation technologies (5.3%), heat generation technologies (4.2%) and infrastructure (3.2%). These trends are similar for the different scenarios in 2035.

Surprisingly, spending in the private mobility sector, in other words the purchase of cars, accounts for €16.2 billion per year and 37.1% of the system's total expenditure. Indeed, in 2015, 5 661 743 cars were registered in Belgium (the equivalent of one car for every two citizens). A further 1 565 422 vehicles were registered, including 781 898 light and heavy trucks, 461 823 motorbikes, 17 067 buses and coaches and 304 634 other vehicles (data from the service public fédéral (SPF) [127]). They estimate housing expenditure for mobility⁶ at around 20.1 b€₂₀₁₅ per year. This estimate cannot be directly compared with the model's estimate. On the one hand, the service public fédéral (SPF) takes into account expenditure on fuel and public transport. On the other hand, it does not take into account expenditure on company cars, which (424 642 cars) are the most used. Overall, the model's estimate (€16.2 billion) is consistent with the actual statistics.

The yearly expenses to buy resources are: 17.9 b€₂₀₁₅/y, mainly for non-renewable ones. The expenses for each non-renewable resources are: natural gas (4.4 b€₂₀₁₅/y), synthetic liquid fuel (4.3 b€₂₀₁₅/y), diesel (3.9 b€₂₀₁₅/y), gasoline (1.5 b€₂₀₁₅/y), electricity imported (1.2 b€₂₀₁₅/y), coal (0.5 b€₂₀₁₅/y), uranium (0.3 b€₂₀₁₅/y) and waste (0.2 b€₂₀₁₅/y).

The electricity production technologies represents an expense of 2.3 b€₂₀₁₅/y, half of it for the nuclear power plants. Most of the expenses in the heating sector represents the decentralised boilers (1.4 b€₂₀₁₅/y), followed by technologies to produce industrial heat (0.35 b€₂₀₁₅/y) and finally centralised technologies for low temperature heating (0.06 b€₂₀₁₅/y). The cost of storage technologies is negligible (0.01 b€₂₀₁₅/y), as only 5 GWh of pumped hydro storage (PHS) is installed. The expenses in the infrastructure mainly represent the power grid expenses (1.6 b€₂₀₁₅/y). Indeed, the cost of the power grid is accounted for with a lifetime of 80 years. Its total investment cost is estimated around 80 b€₂₀₁₅, see details in Appendix C.3.6. It results in a significant annualised cost significant.

Electricity generation technologies account for 2.3 b€₂₀₁₅/y, half of which is spent on nuclear power plants. Most of the expenditure in the heating sector is on decentralised boilers (1.4 b€₂₀₁₅/y), followed by industrial heat generation technologies (0.35 b€₂₀₁₅/y) and finally centralised low temperature heating technologies (0.06 b€₂₀₁₅/y). The cost of storage technologies is negligible (0.01 b€₂₀₁₅/y), as only 5 GWh of pumped hydro storage (PHS) is installed. Infrastructure expenditure mainly represents the one related to the electricity grid (1.6 b€₂₀₁₅/y). The cost of the electricity network is accounted for with a life span of 80 years. Its total investment cost is estimated at approximately 80 b€₂₀₁₅ for 2015, see details in Appendix C.3.6, resulting in a significant annualised

⁶In 2015, expenditure per dwelling was approximately €4 100 per year. They estimate that a dwelling is made up of an average of 2.3 people, and that the population was 11.24 million. Statistics from the service public fédéral [127].

cost.

Scenarios in 2035

Compared to the expenditures in 2015, those of the scenario in 2035 are similar for high emissions. Three differences can be highlighted: the cost of mobility, the cost of infrastructure and the cost of power generation. Between 2015 and 2035, the mobility strategy changes: public mobility is deployed at its maximum (50% of total passenger mobility), it leads to higher expenditures for buses, trams and trains. This result was expected, as the total cost of ownership (TCO) of private mobility was an order of magnitude higher than that of public vehicles (see Section 4.3.3). The infrastructure cost takes into account the networks (electricity and DHN), but also the efficiency measures taken between 2015 and 2035 to reduce end-use demand. These measures, accounted in the model, cost the system 3.2 b€₂₀₁₅, which explains the increase from €1.6 billion to around 5 b€₂₀₁₅ for infrastructure technologies. Finally, the cost for power generation technologies is reduced compared to 2015. Indeed, the system relies mainly on CCGTs which have a low CAPEX.

As observed in the previous Pareto (Figure 5.3), the total cost of the system first decreases and then increases. Figure 5.7 gives more details about this behavior and verifies the following statements. Firstly, the use of efficient technologies implies a reduction in resource expenditure faster than the increase in technology expenditure. Secondly, as CO₂ emissions decrease, the system is forced to phase out fossil fuels and replace them by additional PV capacity. However, as the potential is limited, the system cannot reduce its emissions below 45 MtCO₂/y. At these emissions, the expenses for power generation technologies become significant (11% of total cost) and represents the massive deployment of intermittent renewables, mainly PV (12.7 b€₂₀₁₅/y) and wind turbines (1.2 b€₂₀₁₅/y). However, a capacity of CCGTs is still available to compensate the integration of these renewables, it represents a budget of 0.5 b€₂₀₁₅/y for the technology. Technologies for the production and storage of synthetic fuels are introduced for all scenarios. At first, steam methane reforming is being installed to produce hydrogen. Then, wet biomass is gasified in biomethanisation plants. At the same time, up to 6 GW of electrolyzers are installed to facilitate the integration of the 60 GW of PV. Storage technologies are installed for all scenarios, but their cost - up to 0.23 b€₂₀₁₅/y - is almost negligible compared to the rest.

5.3.2 Cost per sectors

Similarly to Figure 5.7, Figure 5.8 shows the costs of the different scenarios and compares them to the costs in 2015. To avoid double counting, the costs of resources is accounted in the first sector it is used. This implies that the cost of a NG used to produce electricity, and then partially used in DHN heat pumps, is fully accounted in the electricity sector rather than split with the DHN one.

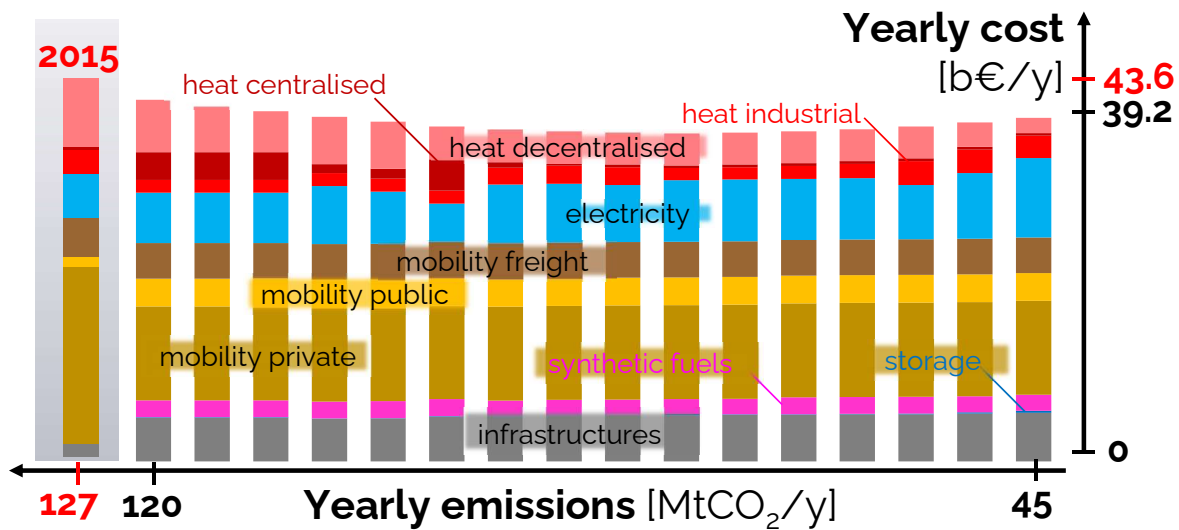


Figure 5.8 – Total annualised cost per sectors for different scenarios in 2035 compared to 2015. The costs are broken down by sector.

When accounting for the resource cost, the heat and electricity sector costs become more important. It reflects the high OPEX part of these sectors. The ratio between the OPEX and the CAPEX varies a lot per sector. In 2015, it is estimated between 0.23 for private mobility sector, up to 8.0 for the production of high temperature heat. For the electricity sector, the resources consumed to produce electricity in 2015 are estimated at 2.6 b€₂₀₁₅, from which 1.3 b€₂₀₁₅ for electricity imports, 1 b€₂₀₁₅ for NG for CCGTs and 0.3 b€₂₀₁₅ for Uranium.

Trends are similar when reducing the GHG emissions: the mobility sector costs are driven by the cost of the vehicles, where in the heat and electricity sector, the cost is driven by the purchase of resources. A small change appears at lower CO₂ emissions. The electricity sector installs PV and wind turbines, resulting in an increasing CAPEX but lowering the OPEX. It results in an increasing cost for the electricity sector.

Compared to 2015, the synthetic fuels are more used. It reflects the hydrogen produced from steam methane reforming to supply the private mobility sector. The centralised heat sector may appear odd around 95 MtCO₂. This is a result of linear programming where two strategies result in a similar cost. In other words, producing dispatchable electricity with CCGTs has almost the same cost than co-producing low temperature heat and electricity in centralised CHP. In the neighbouring scenarios, the first case has been chosen, while at 95MtCO₂ the second solution was chosen. This intrinsic behaviour of LP problems motivates the need for sensitivity analysis.

5.4 What are the options?

Based on the known RE potential (with a limit on solar) and on the energy demand forecast by the European commission [89], the lowest emissions Belgian could reach are around 45MtCO₂ per year, in other words a 65% reduction compared to 2015, or 71% reduction compared to 1995 [132]. In that case, the energy system needs around 330 TWh/y of primary energy, from which 46% are renewable (154 TWh) and 54.0% are fossil (180 TWh). At this stage, the following question arises: what are the possibilities to decrease even more the CO₂ emissions and reach a energy-sustainable system?

5.4.1 Belgian alternative scenarios

One could wonder what are the missing stones to achieve a low emissions society and phase out fossil fuels? Are there any other options which were not accounted for? In the previous sections, we analysed a reference scenario accounting for the known energy potential. In the following, we propose to investigate alternative scenarios where potentials are increased artificially: additional solar, additional offshore wind, geothermal (for electricity and heat production). Moreover, three additional options are proposed: nuclear power (up to the existing capacity in 2020: 5.6 GW), imports of carbon-neutral electricity and imports of renewable fuels. The different scenarios are summarised as follows:

1. **Solar** - *abundant solar*: we assume a potential of 2 864 km² corresponding to 10% of the Belgian land area (see footnote ¹).
2. **Nuclear** - *new nuclear*: we assume that new nuclear power plants can be built up to the existing capacity: 5.6 GWe.
3. **Geothermal** - *geothermal potential*: we assume that Belgium has a geothermal potential that can produce 2 GW of electricity (according to [101], in line with the transmission system operator [100]) and another 2 GW of heat available for DHN.
4. **Wind** - *extra territorial offshore*: we assume that Belgium can access to an additional potential of 3.5 GW in the North Sea.
5. **Elec.** - *carbon-neutral electricity imports*: we assume that neighbouring countries can supply carbon-neutral electricity at any time and at a constant cost of 84.3€₂₀₁₅/MWh_e. In addition, the import capacity is doubled and up to 19.44 GW of simultaneous import is allowed. Finally, politicians agree to be more dependent on their neighbours with up to 50% of the electricity end-use demand that can be imported (30% in other scenarios).
6. **RE-fuels** - *allow RE-fuel imports*: the importation of renewable fuels is allowed, including bioethanol, biodiesel, SNG and H₂ (see Section 4.1).
7. **Mix** - *mix between the technologies*: all the options are implemented.

No scenario with a decrease in end-use demand has been investigated. Indeed, the simplest way to

reduce our emissions is to reduce our EUD. However, this scenario won't be analysed as the amount of energy that can be reduced is controversial and requires a dedicated study. Such a scenario won't be studied in this chapter. However, in Appendix D.3, the marginal cost of the demand have been estimated for different emission targets. results show that reducing the EUD can be a profitable option to mitigate a significant cost increase in the different sectors.

5.4.2 Comparison of the alternative scenarios

A cost comparison between the alternative scenarios is proposed in a Pareto frontier graph, see Figure 5.9. They are compared to the reference scenario. The reference scenario is defined as the one presented in the previous sections with limited solar.

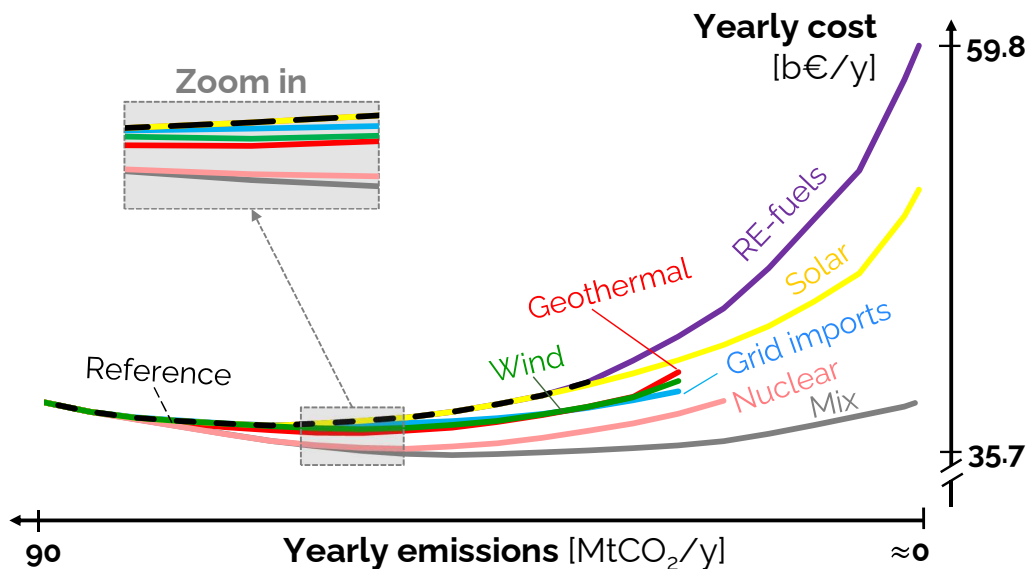


Figure 5.9 – Cost - CO₂ emissions optima for the alternative scenarios. The curves are independent (i.e. they are not stacked). Only the **Mix** scenario achieves nearly 0 emissions (only emissions from uranium, wood and wet biomass remain, for a total of 3.85 MtCO₂/y).

In Table 5.1, the scenarios are compared in terms of: (i) extra capacity and production; (ii) the CO₂ optimum case; (iii) the cost optimum case. This table shows that - a priori - none of the additional local potential (except solar) is sufficient to replace the remaining fossil fuels. Two scenarios, **Solar** and **RE-fuels** achieve low CO₂ emissions but with a high increase in the system cost. **Solar** has been studied in Section 5.1 and **RE-fuels** strategies is to switch from fossil fuel to its equivalent renewable ones. Thus, the cost increase reflects the higher price of the renewable fuel. This solution appears more expensive than integrating massively **Solar**.

By allowing other technologies, as proposed in the scenarios (**Elec.**, **Wind**, **Nuclear** and **Geothermal**), the system cost is lowered. In addition, these scenarios can defossilise a little bit more the system

5.4. What are the options?

Table 5.1 – Model results for cost optimum alternative scenarios. The extra capacity is expressed in terms of power installed and yearly production. Results are detailed in terms of yearly emissions (Emissions), yearly cost (Cost) and the remaining amount of fossil used per year, excluding waste and uranium (Fossils).

	Ref	Sol.	Nuc.	Geo.	Wind	Elec.	fuels	Mix	Units
Capa. extra	-	678	5.6	2+2 ^a	3.5	9.44	-	-	[GW]
Prod. extra	-	670	41.7 ^b	31.5 ^c	23.5 ^b	18.4 ^b	∞	∞	[TWh/y]
CO₂ optimum:									
Emissions	40	3.4 ^d	25	30	30	25	3.4 ^d	3.8 ^d	[MtCO ₂ /y]
Cost	40.0	51.3	38.9	40.6	40.0	40.8	59.8	38.8	[b€/y]
Fossils	115.9	0	170.6	59.6	58.0	81.0 ^e	0	0	[TWh/y]
Cost optimum:									
Emissions	75	75	60	65	65	75	75	55	[MtCO ₂ /y]
Cost	37.5	37.5	36.1	37	37.2	37.5	37.5	35.7	[b€/y]
Fossils	250.4	244.9	183.5	200.5	202.9	252.3 ^f	244.9	175.6	[TWh/y]

^a2 GW of electricity and 2 GW of heat produced by geothermal energy.

^b TWh of electricity.

^cHalf of electricity, half of heat.

^d The remaining emissions are related to uranium (0.4 MtCO₂/y), waste (2.7 MtCO₂/y), biomass (0.7 MtCO₂/y) and uranium (0.4 MtCO₂/y)

^eFrom which 45 TWh are electricity imported.

^fFrom which 13 TWh are electricity imported.

compared to the reference case. However, they cannot reach emissions lower than 35 MtCO₂/y (and 30 MtCO₂/y for **Nuclear**). By allowing all the technologies, as proposed in **Mix**, the system cost decreases and reach an optimum at around 40 MtCO₂/y.

5.4.3 The synergy between different technologies

As none of the technologies (except solar) can bridge the gap, we propose to analyse the **Mix** scenario which has two benefits. First, it achieves low CO₂ emissions at an affordable cost. Second, it appears as the cheapest option at any stage, in other words, the system does not rely on one cheap technology, instead it takes advantage of the synergies between technologies to supply the EUD at a cheaper cost.

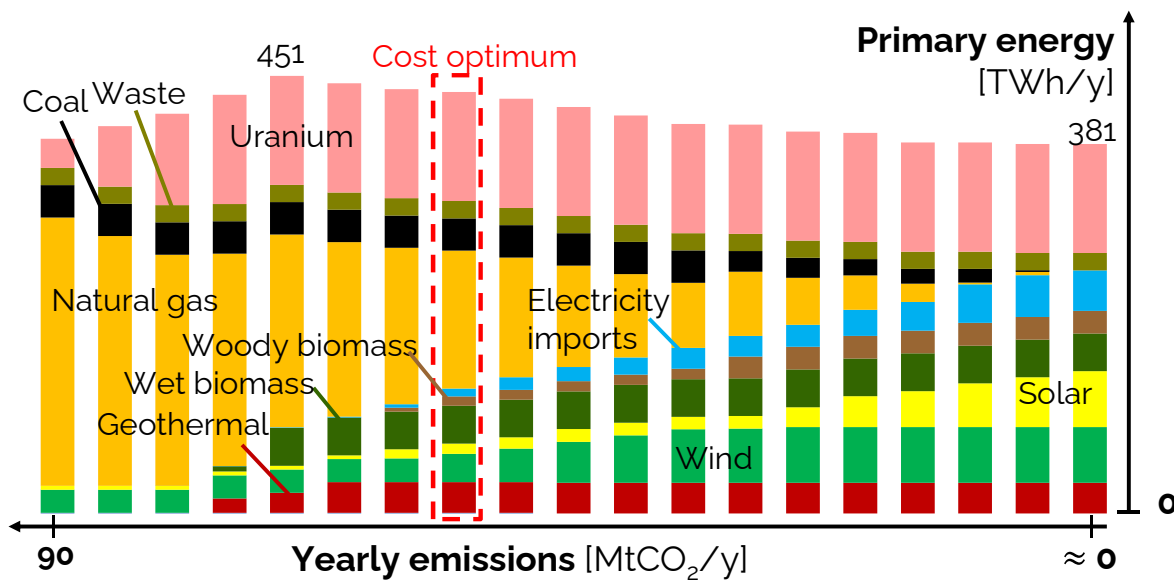


Figure 5.10 – Primary energy supply for the **Mix** scenarios. At the lowest emissions, only emissions from uranium, waste and biomass remain, for a total of 3.9 MtCO₂/y.

Similarly to Figure 5.2, Figure 5.10 represents the resources used when reducing the GHG emissions. We observe similar trends, such as the coal and gas used at high emissions. By crossing the information of Figures 5.9 and 5.10, one would observe that nuclear, geothermal and wind power plants can simultaneously decrease the system cost and emissions. Indeed, the cost optimum is reached after full deployment of onshore wind, geothermal and nuclear. When the CO₂ emissions are lower than 30 MtCO₂/y, local renewables (except solar) are fully deployed and their intermittency becomes an issue. The latter is faced by importing electricity during scarcity and electrolyzers and/or curtailment during excesses. At lower CO₂ emissions solar combined with imported electricity phase out the remaining fossil fuels.

In the carbon-neutral scenario, most of the primary energy is transformed into electricity (214 TWh/y),

compared to heat (56 TWh/y) or other energies (38.9 TWh/y). Half of the electricity is used for end-use demand, one fourth for heat production (mainly low temperature) and one fourth for hydrogen production for mobility. More electricity could have been imported, but at a higher cost than wind, geothermal, biomass and waste.

To summarise, to phase out fossils, the **Mix** scenario relies on affordable renewable energies combined with flexible electricity imported and a base load electricity production from Nuclear power plants. However, most of the options proposed in this scenario - and in this section - are speculative, and they rely on many ambitious assumptions about undiscovered resources. The most realistic scenario which achieves carbon neutrality is, thus, the one allowing the import of renewable fuels (**RE-fuels**). Even if it appears as an expensive option, renewable fuels will be necessary to phase out fossil fuels.

Discussion

In this chapter, the different scenarios to defossilise the Belgian energy system have been analysed. Three components to reduce the GHG emissions were identified: energy efficiency, local renewables and imported carbon-neutral energies.

Compared to 2015, the future energy system - with an increasing energy demand - can save primary energy by using more efficient technologies in each sectors. More specifically, heat pumps, cogeneration of heat and power, and electric or hydrogen vehicles. These solutions allow to reduce the primary energy consumption in 2035 by 38% compared to 2015⁷.

Even if Belgium is a small and highly densely populated country (with European standards), its renewable potential is far from being negligible. More than 150 TWh can be yearly produced thanks to, on the one hand: 60 GW of PV, 10 GW of onshore wind turbines, 3.5 GW of offshore wind turbines and around 0.2 GW of hydro-river. And on the other hand, the availability of sustainable and local biomass: 23.4 TWh/y of lignocellulosic biomass and 38.9 TWh/y of digestible biomass. Altogether, it represents just less than 50% of the primary energy needed. Economically, integrating the full local potential will not have a major impact on the system cost. Indeed, additional expenses required for production assets, grid reinforcement, storage capacities ... are almost compensated by savings made when importing less resources. It results, compared to the cost optimum solution, in an extra cost of 1.7b€₂₀₁₅/y, which represents 5% of the total annualised system cost.

The renewable energy potentials in Belgium, except geothermal, are well-known. The results show that no options should be ruled out. But also that, even if different options appear to be implementable, they will have to be deployed in parallel because their synergy is beneficial to the

⁷This results highly depend on the primary energy metric used. In this case, resources for nuclear and fossils; electricity for PV, wind and elec-geothermal; and heat for heat-geothermal.

system.

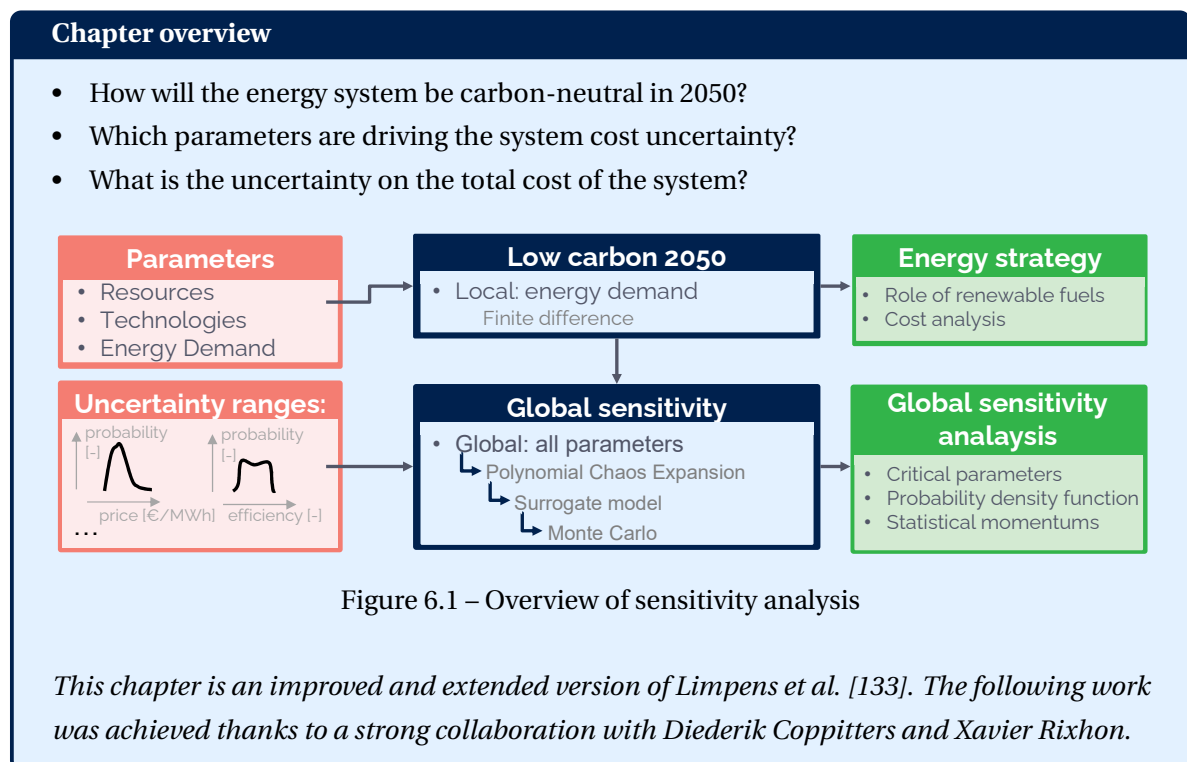
To compensate for Belgium's energy deficit, all options must be maintained, and above all the most realistic one: importing renewable fuels and low-carbon electricity from abroad. More than 150 TWh/y are needed, which represents, assuming baseload imports, a power of 17 GW. Electricity imports will be part of the solution, but they cannot be multiplied by 10 over the next few decades (net imports were between 0 and 21 TWh/year during the period 2005-2019⁸). Thus, renewable fuels will complement imported electricity to phase out fossil fuels.

From a cost perspective, the vehicles expenses is leading the cost. And more particularly the purchase of private cars. it represents a constant annual cost around 50% of the total regardless the GHG emissions target. It is followed by the purchase of fossil fuels. Surprisingly, even if the full potential of PV and wind turbines are deployed, the total cost of the electricity sector represents no more than 15% of the total cost.

This chapter identified the most realistic scenario as the one allowing renewable fuel imports from abroad (called **RE-fuels** in the chapter). Indeed, it relies on known potential of local resources, mainly solar, biomass and wind; electricity import from neighbours; and finally renewable fuels imported.

⁸Real data recorded by the FEBEG: www.febeg.be/

6 Sensitivity analysis of the carbon-neutral energy system in 2050



Deterministic models do not account for uncertainty and rely on long-term forecasts for important parameters. Over the long term of energy planning, forecasts often prove to be inaccurate, which can lead to over-capacity and under-utilisation of installed capacities. Although this underlines the need to take uncertainty into account in energy planning, uncertainty has so far rarely been incorporated into energy models. For example, erroneous projections of low natural gas prices and high electricity demand in Europe in the early 2000s stimulated massive investment in power generation, leading to the current situation of overcapacity in the European electricity market, Moret et al. [134]. In their

work they highlighted the relationship between overcapacity and errors in forecasting electricity demand and fuel prices. In current energy planning practice, most models are deterministic and few of them include sensitivity analysis [46, 135]. In his thesis named *Strategic energy planning under uncertainty*, Moret [46] recommends that ‘*a little uncertainty is better than no uncertainty at all*’; which is in line with the statement of Contino et al. [26]: ‘*The real world is uncertain*’ and the solution of energy models ‘*only makes sense if it is robust*’. Thus, sensitivity analysis will be performed on the Belgian case study.

In the literature, different methods exist to perform sensitivity analysis. The global sensitivity analysis (GSA) is the most relevant method when many parameters can interact and are correlated. Compared to local methods, global sensitivity analysis (GSA) considers the effects associated to the interaction between different uncertain inputs. According to Zhou, Lin, and Lin [136], “*a sensitivity analysis is considered to be global when all the input factors are varied simultaneously and the sensitivity is evaluated over the entire range of each input factor*”. In a previous version (EnergyScope monthly), a global sensitivity analysis (GSA) method has been applied: the “*elementary effect method*” developed by Morris [137]. This is an effective way of sifting through model’s parameters and identify the non-influential ones. This method requires numerous model evaluations, which was affordable with the monthly version of the model (less than one second per evaluation). However, an hourly resolution is mandatory for the analysis of energy systems with a high penetration of intermittent renewable energy. As a result, the computation time is longer, and performing a GSA requires a method that involves fewer evaluations. The polynomial chaos expansion (PCE) method, described in Section 6.2, appears as a good candidate as it is a computationally-efficient surrogate modelling technique which efficiently provides the statistical moments and sensitivity indices (i.e. Sobol’ indices) [138]. This method has been applied successfully to other energy systems, such as a power-to-ammonia system [139], a micro-gas turbine with carbon capture [140], or a hydrogen-based energy system [141].

The previous chapter analysed different scenarios to defossilise the Belgian energy system. General trends were extracted, such as the deployment of efficient technologies or the massive use of local renewable resources. However, in order to defossilise completely, only one scenario was realistic: the one based on the import of renewable fuels. In this chapter, this scenario is examined in the light of a GSA. A special attention is paid to the long-term objective of the energy transition: a carbon-neutral energy system by 2050.

Contributions

This chapter presents a realistic and almost carbon-neutral Belgian energy system in 2050. The energy and investment strategies will be illustrated in terms of primary energy used, technologies deployed and cost related to each sector. To compare its competitiveness with fossil-based systems,

the results are compared with the ones where GHG emissions are allowed.

Once the behaviour of the carbon-neutral scenario is understood, a GSA will be performed for the different emission targets. The parameters causing the uncertainty will be listed and their impact on the total cost of the system will be quantified. The importance of these parameters varies during the transition. Finally, the probability density function of the total system cost will be calculated. All these results are later translated into policy guidances.

6.1 Energy systems in 2050

Compared to the previous cases, the energy system is studied in 2050 (rather than 2035). They are four minor changes in the parameters used: imported electricity is more expensive and its emission intensity is zero¹; technologies are more efficient and their costs usually decrease²; imports of renewable fuels are more affordable; and, yearly end-use demand rises slightly, except for the one of high-temperature heat which decreases. These differences were previously depicted in the case study, Chapter 4.

According to the ‘*Green deal*’ ambition, the Belgian energy system must achieve carbon neutrality by 2050. In this scenario, it remains a small amount of emissions due to biomass ($\approx 0.7 \text{ MtCO}_2$) and waste use ($\approx 2.7 \text{ MtCO}_2$). As a reminder, the emissions are related to the resources which accounts for the impact associated with production, transport, and combustion (see Section 4.1.3). For the sake of simplicity, this lowest emission scenario is called *carbon-neutral*.

To link up with previous the results, the energy system in 2050 will be studied for different GHG emission targets and for near-zero emissions. The energy system will first be analysed in terms of primary energy mix and yearly cost. Then, a focus will be made on the carbon-neutral case.

6.1.1 Primary energy and system costs

The scenarios range between emissions of $72.2 \text{ MtCO}_{2\text{eq.}}/\text{y}$ and $3.4 \text{ MtCO}_{2\text{eq.}}/\text{y}$. The higher bound represents the cost optimum scenario, where the lowest bound represents the lowest emissions reachable.

Figures 6.2 (a) and (b) show the primary energy consumed and costs by sector for the different scenarios. The evolution of the primary energy consumed is similar to the one studied in the previous chapter, in 2035: at first, gas and wind are used, then more efficient technologies decrease the primary energy consumed; on the meantime, the remaining local renewable potential is fully

¹Neighbouring countries are assumed to also become carbon-neutral.

²They are some exceptions. The most notable one are cars powered with internal combustion engines. The regulation forces to reduce emissions, which results in more expensive filters (detail in Section 4.3.1).

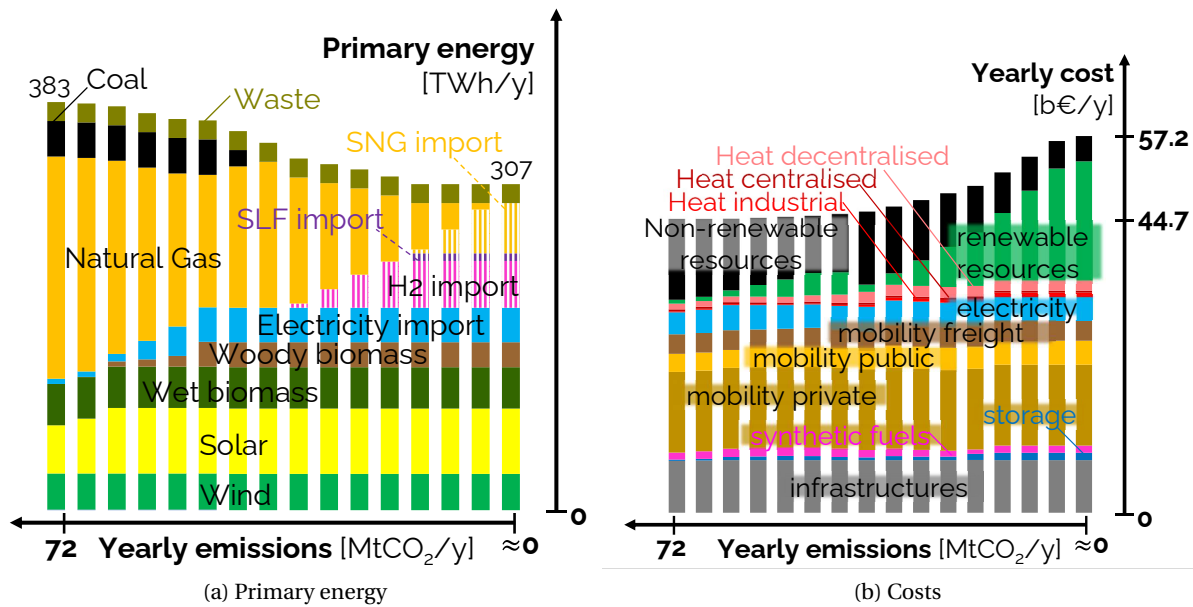


Figure 6.2 – Primary energy supply (a) and costs by sectors (b) for the different GHG emissions scenarios in 2050. The energy are broken down by resource types. The costs are broken down by investments per sector, and resources.

exploited, and finally imported renewable fuels substitute the fossil ones. Compared to 2035, they are three nuances: deployment of PV, imports of electricity, and imports of renewable fuels. The technology costs of PV and battery are reduced by 27% and 48%, respectively, over the period 2035-2050. As a consequence, the full potential of PV is reached at higher emissions in 2050 (65 MtCO₂) than in 2035 (45 MtCO₂). The imported electricity emission intensity is assumed negligible in 2050, thus this resource is imported in the carbon-neutral solution. The imports of renewable fuels are cheaper, but still more expensive than the equivalent fossil ones. However, the system has no choice than importing these fuels to defossilise the system.

From a cost perspective, the trends are also similar to what has been observed for 2035. The only two differences are: the replacement of fossil fuels by renewable fuels, and the greater use of storage technologies. At 50 MtCO₂/y, all the endogenous renewable potential and the maximum amount of imported electricity (≈ 33 TWh/y) are used. Thus, the system has no choice but to replace imported fossil fuels (158 TWh/y) with imported renewable fuels. As a result, the cost of the system increases. An additional storage technology is deployed: batteries. Its investment cost should decrease considerably compared to current prices (see Section 4.3.1). Thus, the system deploys batteries to store excess electricity from midday to night. This system allows a reduction of 2 TWh/y of curtailment compared to the solution proposed in 2035.

The energy system in 2050 is - on average and for the same emissions target - 14% more expensive

than the one in 2035. As an example, for the case of 45 MtCO₂/y emissions, the annual system costs are 39.2 b€₂₀₁₅/y in 2035 compare to 45 b€₂₀₁₅/y in 2050. The difference mainly comes from the increasing prices of fossil resources and the efficiency measures to reduce the yearly EUD over the period. These measures, described in Section 4.2.1, account for a total budget of 2.4 b€₂₀₁₅ over the period 2035-2050.

6.1.2 Carbon-neutral system

The target for 2050 is the carbon-neutrality and the defossilisation of the energy system. This scenario is analysed in more details as it represents the final objective of the transition. A Sankey diagram (Figure 6.3) gives an overall picture of the annual energy balance.

Unsurprisingly, the system uses the maximal endogenous potential of renewable resources: solar (61.5 TWh/y), digestible biomass (38.9 TWh/y), wind (33.9 TWh/y), wood (23.4 TWh/y) and hydro (0.5 TWh/y). Altogether, they provide 52% of the 307 TWh/y of the primary energy needed. The remaining part is covered by imported renewable fuels (32%), electricity (11%) and waste (6%). renewable fuels are expensive, however they are the only resource still available at this stage of the transition. Thus, the system uses: synthetic natural gas (SNG) (47.2 TWh/y) for balancing electricity production of intermittent renewable through dispatchable assets; hydrogen (44.0 TWh/y) for private and freight mobility; and synthetic liquid fuel (SLF) (7.2 TWh/y) for public and freight mobility.

Storage and flexible units are installed to deal with intermittent renewables. Battery price has drastically reduced compare to 2015 and is now competitive. As a consequence, 80 GWh of batteries are daily used to shift the excesses of PV production (59 GW installed) to the night. In addition, the electrification of the heat sector combined with thermal storage - mainly low temperature - plays a role as a flexible electricity consumer. To compensate the lack of electricity production, 3.2 GW of CCGT and 3.5 GW of gas-CHP are installed. These units are often used with a capacity factor of 59% for CCGT and 83% for gas-CHP.

From an economical point of view (Figure 6.2b), the expenses are split into resources purchase (38%), vehicle costs (33%), infrastructure and efficiency measures (14%), electricity sector (6%), heat sector (5%)), and the rest (4%) equally split between storage and synthetic fuel production technologies. The expenses in the sectors are related to the investment in the conversion technologies and do not account for the use of resources.

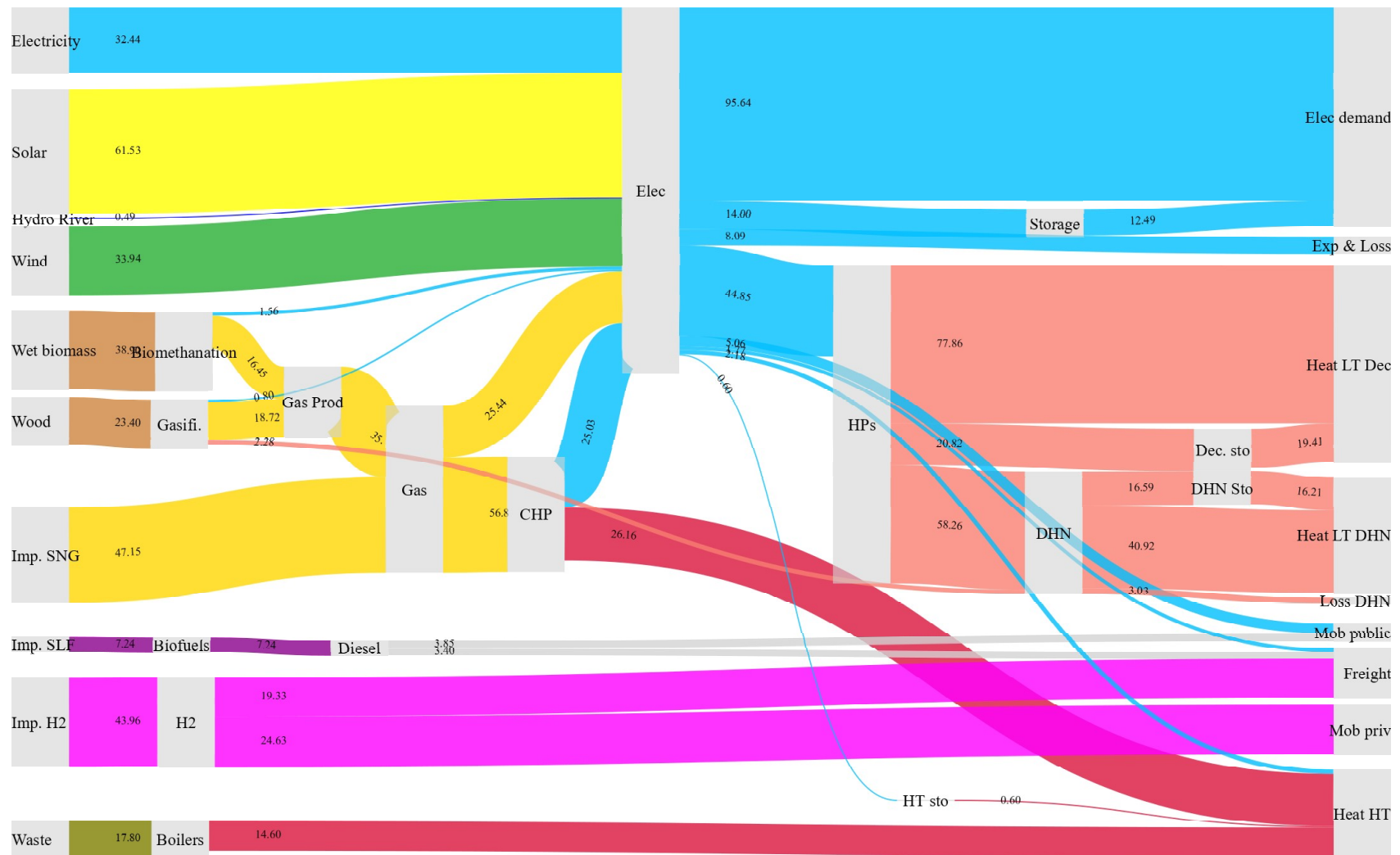


Figure 6.3 – Energy flows in a scenario representing a carbon-neutral Belgian energy system in 2050. The left side gathers all the resources and the right side gathers the final energy consumption. In between, the conversion technologies. Abbreviations: cogeneration of heat and power (CHP), district heating network (DHN), electricity (Elec), Export (Exp) hydrogen (H₂), heat pump (HP), import (Imp) low temperature (LT), high temperature (HT), mobility (mob), natural gas (NG), private (priv), synthetic liquid fuel (SLF), synthetic natural gas (SNG), storage (sto.).

6.2 Sensitivity methodology overview

This section provides an overview of the framework used to perform the GSA (Appendix D describes the overall methodology). Figure 6.4 represents how the polynomial chaos expansion (PCE) framework is built and used. First, parameter uncertainties are characterised. Second, the polynomial chaos expansion (PCE) framework is applied to the model and a surrogate model is built. Third, based on this surrogate model and multiple model evaluations, the ranking of the uncertain parameters and the system costs statistical momentums are extracted and analysed.

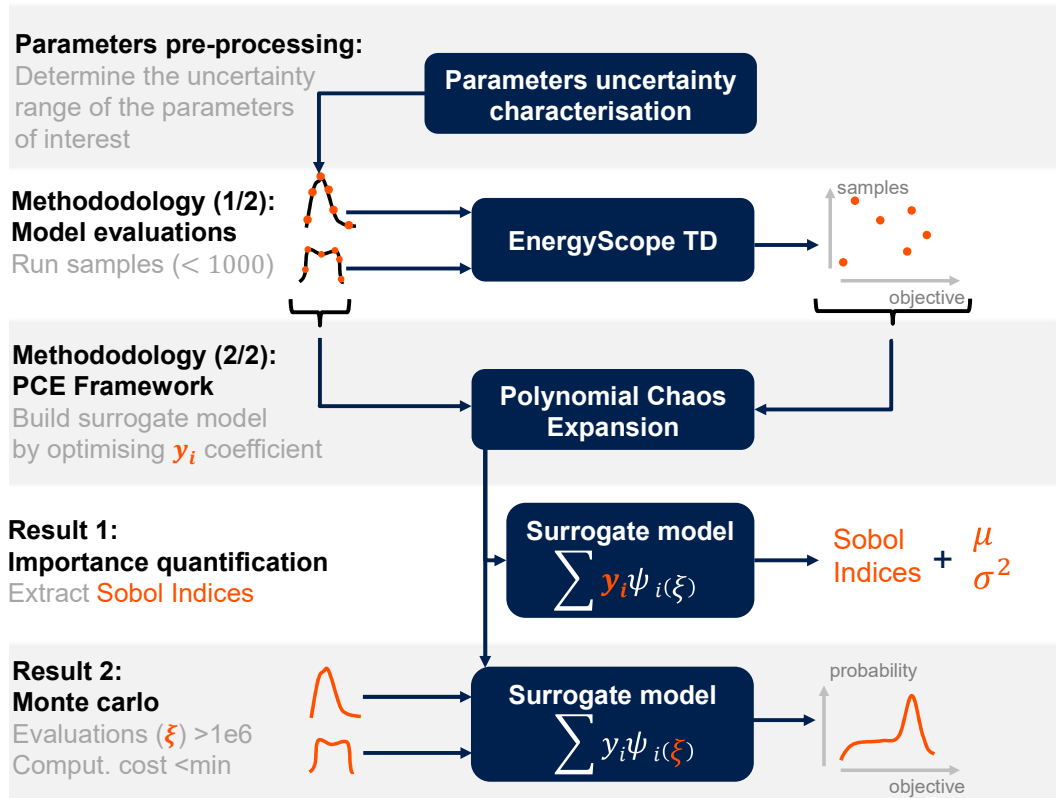


Figure 6.4 – Overview of the Polynomial Chaos Expansion implementation and results. Abbreviations: typical day (TD), polynomial chaos expansion (PCE). Symbols: polynomial (Ψ_i), polynomial coefficient (y_i), set of parameters (ξ), average (μ) and variance (σ^2).

The uncertainty characterisation gives the uncertainty ranges per parameter or group of parameters. Indeed, some parameters are correlated *a priori*, such as the laboring cost for maintenance, or the price for cars running on gasoline or diesel. In the literature, Moret et al. [142] performed an uncertainty characterisation of the energy system parameters. The model used was the monthly version of the EnergyScope model, and the case study was the Swiss energy system. Based on their work, the characterisation has been extended to the new model and the Belgian energy system. It results in 122 groups of parameters with their uncertainty (see Appendix D.1 for further details and numerical values). As the case study is in 2050, nuclear and geothermal energy should not be

allowed and therefore not included in the GSA study. Indeed, Nuclear is not extended after 2025 and geothermal potential is unknown. However, in the previous Chapter (see Section 5.4.2), these technologies appeared as efficient options to both reduce the system cost and its emissions. Thus, we allow Nuclear to be installed with a capacity limited to that of today (5.6 GW) and Geothermal with a potential of 2 GW_e for electrical production and 2 GW_{th} for district heating network.

The method for performing the GSA is called polynomial chaos expansion (PCE). In a first step, samples of uncertain parameters are evaluated in the model. This results in a set of parameters-results used to build a surrogate model. This PCE method builds a series of multivariate orthonormal polynomials, where the polynomial family for each univariate polynomial depends on the distribution of the uncertain parameter. By optimising the coefficient values, the PCE method minimises the euclidean distance between the polynomial estimation of the result and the real model result. Depending on the number of sets, the order of the polynomial can be increased and is therefore more accurate. For tens of uncertain parameters, a few hundred evaluations are necessary to have a first-order polynomial, while more than one hundred thousand evaluations are necessary to have a third-order polynomial. Based on the coefficient of the surrogate model, it is possible to extract statistical momentums. Once the surrogate model has been constructed, it can be used to carry out a Monte-Carlo evaluation. Millions of samples are generated and the associated results can be calculated instantaneously on the basis of the surrogate model. It allows the precise calculation of a probability density function (PDF) of the total annualised cost of the system.

The analysis of the polynomial coefficients allows to calculate the Sobol' indices for each parameter. The Sobol method decomposes the variance of the model output (total system cost) into fractions that can be attributed to each uncertain parameter. It is therefore an indicator of the influence of the uncertainty of a parameter on the uncertainty of the output, and thus how critical is the parameter on the output variance. Analysing the total system cost PDF gives some insight into the robustness of the solution. The shape and the spread of the PDF are meaningful and can be translated into political guidance.

6.3 Application to the energy system in 2050

The framework has been applied to scenarios at different levels of GHG emissions. At first, the critical parameters of these scenarios are analysed. Then, the focus is shifted to the carbon-neutral energy system and a broader study, in terms of parameters, is carried out. Finally, the probability density functions are generated for the different scenarios.

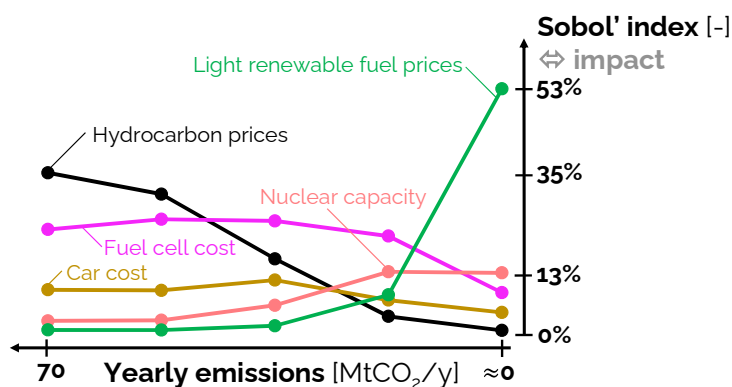


Figure 6.5 – Top-5 of critical parameters for the different scenarios.

6.3.1 Critical parameters

Figure 6.5 shows how the parameter Sobol's indices vary according to the scenarios. Only the *critical* parameters are shown. A parameter is deemed '*critical*' if it has a significant Sobol index, i.e. if its uncertainty has a significant impact on the total cost variance. As a good practice, the threshold value is set to one divided by the number of parameters.

A preliminary study has been carried out on the 122 uncertainties of the parameters, or family of parameters, in order to determine which ones had no impact (details in Appendix D). In the following, no distinction will be made on a parameter or a family of parameters. Out of the study, a shorter list of 43 parameters was identified. And, of these 43 parameters, five of them are dominating over the transition: the price of hydrocarbons, the price of light RE fuels (e.g. H₂ or SNG), the cost of fuel cells, the cost of cars and the maximal nuclear capacity. The Sobol indices of these parameters are illustrated in Figure 6.5. Table 6.1 shows the uncertainty characterization for these parameters and their maximum value of the Sobol index over the scenarios. The prices of imported renewable fuels are gathered into two families: *light* and *heavy*. *Light* qualifies imported hydrogen, methane and methanol (also called synthetic liquid fuel (SLF)). Where, *heavy* qualifies imported bio-diesel and bio-gasoline.

Depending on the permitted GHG emissions, the values and ranking of the Sobol indices change. This happens mainly for the resource prices. Unsurprisingly, at higher emissions, the prices of imported hydrocarbons dominate, while at low emissions, the prices of imported light RE fuels dominate. As an illustration, this latter parameter drives - by far - the uncertainty (53%) for the carbon-neutral case. This uncertainty affects the price of imported H₂, SNG and SLF. This importance can be justified with three arguments: first, there is no alternative to renewable fuels to defossilise the Belgian energy system (see Figure 6.2b). Second, renewable fuels are expected to be more expensive than today's fossil fuels; and thus, they have a more important contribution in the total system cost. Third, the uncertainty on future renewable fuels prices is high. All combined, it

Table 6.1 – Uncertainty characterisation for the critical parameters. Except for Nuclear, the uncertain parameters regroup a family of parameters: hydrocarbon prices (hydrocar.), such as light fuel oil or NG; fuel cell (FC) costs account for the vehicles powered by this technology; light RE fuel prices, such as hydrogen or synthetic natural gas; car costs, such as a gasoline car or a diesel one. For the latter parameters, the reference value is one, as the uncertainty is multiplied to the reference value of the parameter.

Parameters	<i>hydrocar.</i>	<i>FC costs</i>	<i>light RE fuels</i>	<i>Nuclear</i>	<i>car costs</i>
Units	[€/€]	[€/€]	[€/€]	[GW]	[€/€]
reference	1	1	1	0	1
min	-47.3%	-39.6	-47.3%	0	-21.6%
max	+89.9%	+39.6	+89.9%	5.6	+25.0%
max Index	34.8%	24.6%	53.2%	13.1%	11.3%

results in a high uncertainty on a major component of the the system total cost.

At high emissions, a similar result appears with hydrocarbon prices. This category accounts for the price of gasoline, diesel, oil, NG and coal. This uncertainty has a lower impact on the Sobol index than the previous one. Indeed, the fossil fuels are expected to be cheaper than the renewable ones. And thus, the impact on the total system cost will be lower.

The next two parameters, in terms of importance, are the investment cost of fuel cells (FCs) and the cost of the private cars. The first one takes into account the uncertainty on technologies using FC, which are: buses, trucks, cars and decentralised CHP. The second takes into account the uncertainty about the production cost of cars. Vehicles have two sources of uncertainty about their investment cost: the type of vehicle and the powertrain. Thus, it is assumed that half of the uncertainty on the vehicle investment cost is related to the uncertainty on powertrain and the other half to the uncertainty on the vehicle. For example, if cars are expected to be much more expensive and fuel cells cheaper, this may result in an unchanged price for the FC car. The range of uncertainty of car investment is low (-21.6% to 25.0%) compared to others. However, its contribution to the cost of the system is significant: between 21 and 28%. Even a small variation in its cost implies a significant variation in the cost of the system. Indeed, the system has no alternative than deploying at least 50% of cars (in terms of passenger mobility supplied). For the uncertainty of FC investment costs, the reason is different. The system can change the powertrain of vehicles. With a high cost for FC, these technologies could be replaced by others. As an illustration for the carbon-neutral case - on the basis of 5000 samples - the private mobility is provided by FC cars (69.8%), electric vehicle cars (17.7%) or hybrid electric vehicle (12.4%)³. The trucks freight mobility is provided FC trucks (81.4%), diesel trucks (13.1%), electric trucks (5.3%) or gas trucks (0.2%). While the uncertainty range is small, it does affect vehicle choices of a significant portion of the mobility sector. In addition, the fueling

³Among the hydrocarbons technologies, the HEV is preferred as it is less energy intensive than others, except plug-in hybrid electric vehicle (PHEV). It is more interesting than PHEV as it is cheaper.

strategy will be adapted and the overall system affected. These have significant impacts on the total cost of the system.

The last critical parameter is the authorised nuclear capacity. As previously motivated, this technology can provide baseload electricity production with negligible GHG intensity. For the low GHG scenarios, this technology is preferred over the gas. Indeed, NG and RE gas are more expensive than uranium by almost two orders of magnitude. With an annual electricity production of around 40 TWh/y, nuclear power can remain a major player in the electricity production mix.

6.3.2 Focus on the carbon-neutral scenario

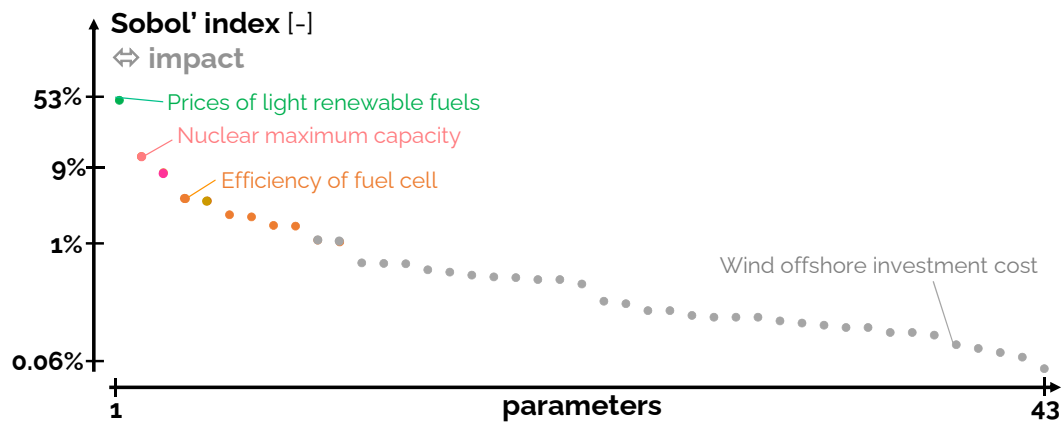


Figure 6.6 – Sobol indices of the parameters for a carbon-neutral energy system. Parameters are sorted and critical ones (in colors) have an index above 2.3% ($= \frac{1}{43}$). The y-axis is logarithmic.

Figure 6.6 shows all the 43 Sobol indices for the carbon-neutral case. Out of them, 9 have an impact greater than 2.3% ($= \frac{1}{43}$) and are qualified as *critical*. The importance of the latter parameters are summarised in Table 6.2.

Table 6.2 – Critical parameters (Sobol' indices greater than 2.3%) and Sobol' indices value.

Parameters	Sobol' Indices [%]
Light RE fuels price	53.2
Nuclear capacity	12.8
Fuel cell price	8.5
Fuel cell efficiency	4.4
Car price	4.2
Labor cost	2.9
Heavy RE fuels price	2.8
Efficiency measures	2.3
Increase of elec. demand	2.3

Out of the parameters previously analysed, only the hydrocarbons price is not kept in the list. The

new five parameters are: the FC efficiency, the labor cost, the heavy RE fuels price, the efficiency measures and the yearly electricity demand. Out of the new parameters, the uncertainty on the FC efficiency has the highest impact. Similarly to the uncertainty of the investment cost of FC, the one for the efficiency is important as it is directly related to amount of hydrogen imported by the system. Similarly to light RE fuels, heavy ones are also a good alternative to defossilise the system. However, light fuels are preferred as they can be used in FC and thus benefit of a higher efficiency compare to heavier fuels. However, under the following circumstances: high prices of light RE fuels, and low price of heavy RE fuels, bio-gasoline can substitutes hydrogen for private mobility. An extra demand of electricity will imply additional production and consequently more electricity production from gas assets. Indeed, the other options are already fully exploited. The investment required for efficiency measures to reduce the EUD are consequent (5.6b€₂₀₁₅) and the uncertainty around them important (-39.3 to 39.3%). The calculation behind are detailed in Appendix C. The labor cost is present when accounting for the maintenance of the installed technologies. If the labor cost increases, the maintenance cost is expected to increase also. The latter is a significant component of the total system cost, as every technologies needs yearly maintenance. For this scenario, 5.48 b€₂₀₁₅ are yearly needed to cover this maintenance. As it is a significant part of the total cost (9.6%), a change in its cost will have an important impact on the energy system cost.

Surprisingly some parameter uncertainties do not appear. As an example, PV and wind turbines are fully deployed, and neither their cost, nor their yearly availability have a significant impact on the total system cost. These technologies are contributing to the total system cost, but their annualised cost - accounted in the electricity sector - are small compared to other sectors, such as mobility (see Figure 6.2b). Other examples are the potential of renewables energies. The Belgian renewable potentials are uncertain and present variations of 5 TWh/y for onshore wind, 3 TWh/y for offshore wind, 15 TWh/y for solar and 20 TWh/y for biomass. Their uncertainties are not critical as they represent less than 15% of the primary energy demand.

6.3.3 Increasing importance of uncertainty

The total cost variation can be illustrated by generating the probability density functions (PDFs) for the different CO₂ emissions. To generate these PDFs, the PCE method achieves the highest computational efficiency: a large sample set (i.e. 1e6 samples) is evaluated on the PCE surrogate model, which requires negligible computational time, as opposed to evaluating these samples on the actual model.

Figure 6.7 shows the bell-shaped PDFs and their standard deviations. In addition, the two curves show the total system cost with the deterministic values and the averaged ones. Defossilising the energy system implies an increasing cost of the system, but not only that, two additional information can be extracted from the PDFs. Taking into account for the uncertainties results in an increased

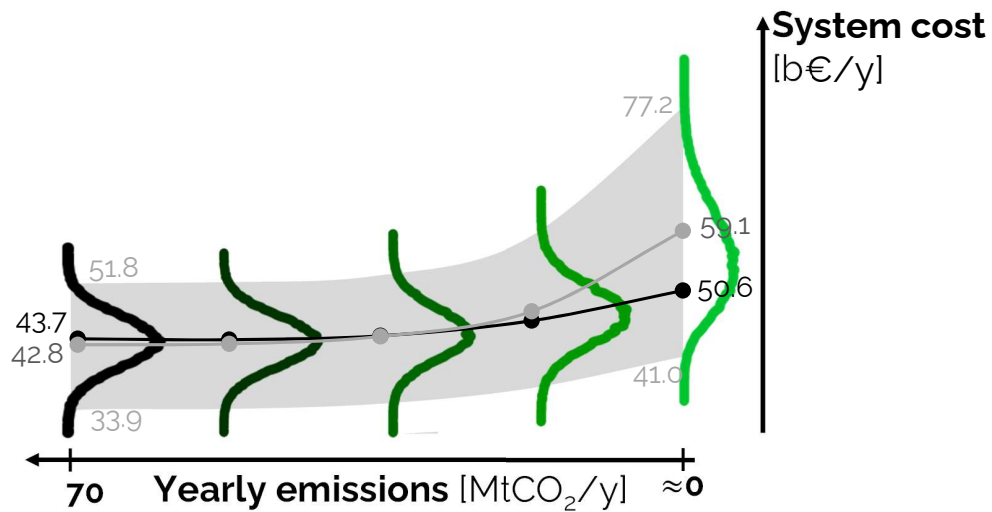


Figure 6.7 – Probability density functions (PDFs) for different GHG emissions. Grey zone represent the standard deviation ($\pm 2\sigma$). Curves represent results with averaged uncertainty (grey) and deterministic values (black).

estimate of the cost of the system. Indeed, at low emissions, results with averaged uncertainty diverge from those with deterministic values. This can be explained by analysing the characterisation. Uncertainty ranges are not always centred, and the averaged values may therefore be higher than the deterministic ones. As illustrated in Table 6.2, it is the case for fuel prices and car costs. In addition, the standard deviation increases as emissions decrease. Thus, the role of the uncertainty about the key objective becomes increasingly important in the transition.

Discussion

The defossilisation of the energy system in 2050 behaves similarly to the one studied in 2035. To drive the country to carbon neutrality, the local renewables are firstly deployed in parallel with imported electricity to facilitate the integration of intermittent renewables. At the end, the remaining fossil resources are substituted by imported renewables fuels.

By applying the PCE framework to scenarios in 2050 at different GHG targets, a list of parameters driving the total cost uncertainty were identified. As a complement, the evolution of this for different emissions was provided. For the carbon-neutral scenario, out of the 122 uncertainty parameters investigated, only nine parameters have a significant impact on the total cost. In particular, the cost and efficiency of fuel cell appears as critical. In the deterministic results, this technology appear as the backbone for defossilising the mobility sector. However, when accounting for uncertainties, electric vehicles and hybrid ones appear also as good candidates.

The impact on uncertainties on the total cost of the system appear to be rising during the transition.

Decision today could mitigate their impact tomorrow and facilitate policy makers to drive our society to carbon neutrality. Hereafter are two examples of measure that could reduce the impact of uncertainties on tomorrow energy system. Subsidising research in the fuel cell field can decrease the uncertainty on their cost or efficiency. Supporting the synthesis of renewable fuels (electro or bio) is another way to reduce the uncertainty on their future costs.

Perspectives

This chapter is a preliminary result of a work in progress that aims at generating robust design of the energy system. The work can be extended by improving the analysis of the results, analysing the impact on other key performance indicators (KPIs) and/or applying a robust design optimisation (RDO) algorithm to minimise the variance of the outputs. The analysis of the results can be extended by taking advantage of the number of solutions generated. Indeed, it is possible to analyse how often a technology is installed, what are the correlations between technologies (e.g. PV and batteries), what are the different strategies (e.g. electric mobility versus hydrogen)... Currently, the study focuses on only one key performance indicator (KPI): the total cost of the system. As proposed by Moret [46], other KPIs could be used: investment strategy, resource supply, total system emissions, etc. Analysing these different indicators would give more depth and insight to the findings. Finally, a robust design optimisation (RDO) would offer a design which is resilient to uncertainty. This approach allows, in addition to optimising the total cost, to minimise the variance of the solution according to different criteria. As a result, the solution will be more resilient in the case of prediction errors.

7 Energy transition pathway analysis

“who fails to plan, plans to fail”

Winston Churchill (adapted from Benjamin Franklin)

Chapter overview

- Application of the Pathway methodology to the Belgian energy system on the period 2015 to 2050.
- Analysis: what are the transition steps? How to comply with the Green deal?

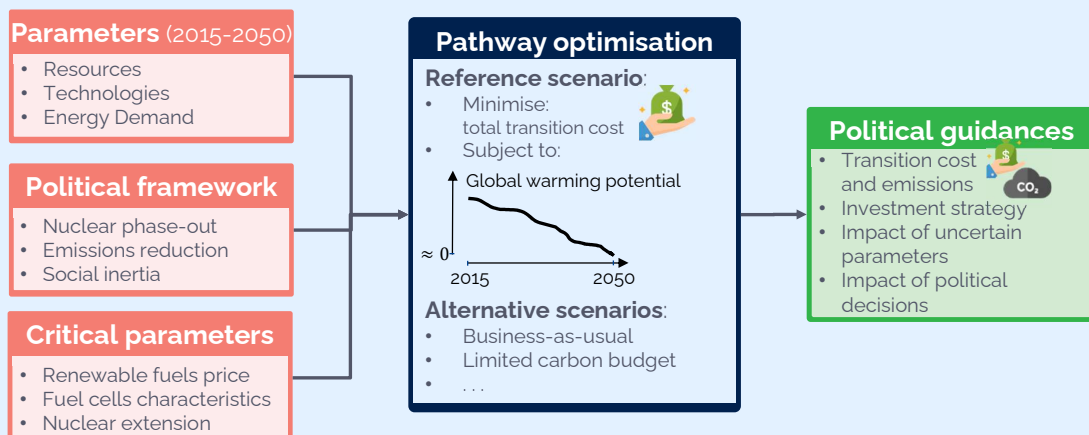


Figure 7.1 – Overview of the energy transition pathway results

The previous chapters identified '*how*' the Belgian energy system could be defossilised. Different methods allow to reach carbon neutrality, such as the use of local renewable resources, use of efficient technologies, electrification of other sectors or imports of renewable fuels. However, it remains the question '*when*' these methods will be deployed between 2015 and 2050. And '*which*' one will be the first. Starting from 2015, will it be more interesting to keep less efficient technologies the longest they can, or to replace them as soon as possible? Which sector should be defossilised first? How the system can phase out nuclear in 2025? All these questions require to link the target objective - carbon-neutral energy system in 2050 - to the existing energy system in 2015.

In the literature, these questions are discussed in reports published by different types of organisations: public agencies, research centres, private companies, etc. Most of the studies focus on a specific sector, a few have a broader view. Most of the studies are focused on the electricity sector. The transmission system operator (i.e. ELIA) frequently gives its opinion on the flexibility and adequacy of the electricity network over the long term [100, 143]. This topic is also of great interest to researchers who are studying, as an example amongs many, the need of storage capacity in order to increase intermittent renewable production up to 50% [144]. The EnergyVille consortium also publishes studies such as the choices and costs of the transition, where they analyse different scenarios for the Belgium energy security and system cost [122]. Likewise, there are studies on the heat sector, such as the Heat Roadmap project which identifies geographical areas where heat networks would be pertinent [129]; or more recently studies focusing on the role of electrofuels in Belgium [145, 146]. However, few studies cover the entire energy system. One is the study led by the Federal Planning Bureau in 2013, based on the TIMES model. In their work, they analyse the energy transition based on several renewable energy scenarios [101]. Another example is the work undergone by Climact [147], which has developed an interactive web calculator [148]. The calculator includes, beyond the energy sectors, other levers such as a reduction in the energy demand.

There are two limitations in the current studies to answer the previously mentioned questions. Firstly, the scenarios are partially detailed - not giving all the data used - and thus limiting the interpretability of the results. Secondly, the models used are rarely open access, preventing an outside party from verifying the methods used and updating/continuing the work. Effective action to mitigate climate change is overdue and there is an urgent need to have consensus on energy policies. Therefore, models need to be transparent and replicable to reduce parallel efforts and allow researchers to collaborate and share their developments [28].

These limitations motivate the development of an open-source pathway model that can answer these questions. Thus, in this Chapter, the pathway methodology presented in Chapter 3 will be applied to the reference case study. First, this reference case study is analysed in order to understand when investments must be done during the transition. Then, the reference case will be compared to other scenarios where no defossilisation is achieved. In addition, the results obtained will be compared with other studies. Finally, the impact of uncertain parameters and political measures

will be assessed in the last section.

Contributions

This chapter illustrates the first application of the EnergyScope pathway methodology to a case study. Thus, the following paragraphs will verify the consistency and feasibility of optimising the energy transition pathway of a whole-energy system country. The results will offer a road-map in terms of primary energy mix, technologies deployment and sector prioritisation over the 35 years of the transition. In addition, key performance indicators, such as the overall cost and GHG emissions, are calculated and used to compare the results with other studies.

In addition, the results are confronted with other scenarios and other studies in the literature to verify the validity of the work. These scenarios enable a deeper analysis of the pathway and qualifies different approaches. As an example, by limiting the carbon-budget, a cost per ton of CO₂ can be estimated. Or, by performing local sensitivity on the critical parameters, an overview of the extreme investment strategies are given.

7.1 How to reach our long term goal?

In the following section, the EnergyScope Pathway model is applied to the case study presented in Chapter 4. This scenario pathway is later called the '*reference*' pathway in contrast to other pathways presented later. In the following, an overview of the emissions per sector and their reduction until 2050 is first given. Then, a focus is made on the representative years in order to understand when technologies are deployed and why. Finally, an analysis of the investment changes during the transition is performed.

Contrary to the previous chapters, the years represented in the graphs are now linked. In order to clearly distinguish these cases, the graphs use areas linking the representative years, rather than using bar charts as it was in previous chapters.

7.1.1 Emissions during the transition

Figure 7.2 shows the greenhouse gas (GHG) emissions per sector. Similarly to the transition observed in Section 5.1, two categories appear: (i) a cost effective energy efficiency and (ii) an expensive defossilisation. Until year 2030, efficiency measures can reduce the system emissions faster than the objectives (this is the gap between the black curve and the red dash). This reflects that the first efforts to reduce emissions are cost-effective. A singularity in the curve is to be noted in 2020. Compared to these neighbouring years (i.e. 2015 and 2025), 2020 can rely on the full availability of nuclear power plants. It results in a dip of 10 MtCO₂/y in the emissions related to the electricity sector in 2020.

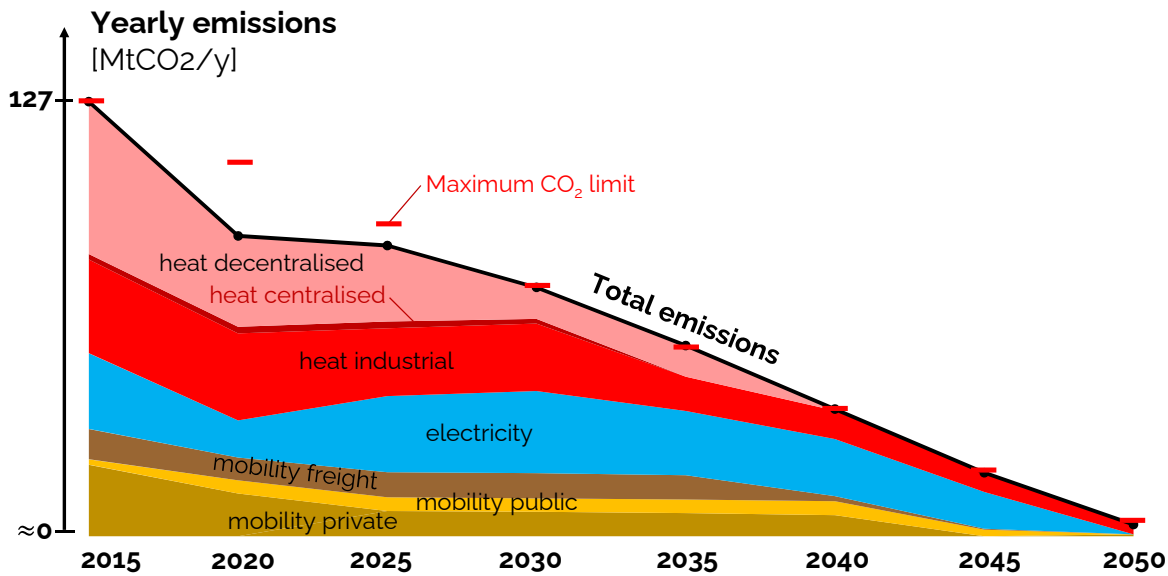


Figure 7.2 – Greenhouse gas emissions per sectors over the transition. The dip in the curve in 2020 represents the return to service of the 7 nuclear power plants, and thus a reduction of the emissions in the electricity sector. The red dash represents the maximum amount of annual emissions allowed by the model.

Compared to 2015, the low-temperature heating and private mobility sectors are the first to reduce their emissions. They achieve carbon neutrality by 2040 for the low-temperature heating sectors and by 2045 for the mobility sectors. A significant share of emissions is committed for the electricity sector until 2050. These changes in emissions are directly linked to a change in the technologies and the fuels used. In the following section, these changes will be investigated on a sector-by-sector basis.

During this transition, Belgium emits a total of 2.24 GtCO₂ equivalent. This accounts for emissions related to resources (production, transport and combustion), but do not account for technologies embodied emissions, such as the construction of a wind turbine or a car manufacturing.

7.1.2 Defossilisation steps

To decipher and understand the optimised transition strategy, a focus is given on the primary energy. This drives us to the challenges of phasing out nuclear, the importance of electrification and the role of the renewable fuels.

Primary energy used

Similarly to the scenarios analysed previously, Figure 7.3 gives the primary energy distribution over the different years. The pathway method verifies trends highlighted in the previous result sections (Section 5.1): (i) reduction of primary energy needed thanks to energy efficiency; (ii) key role of gas; (iii) importance of electrification; and (iv) the obligation to rely on renewable fuels to achieve carbon neutrality.

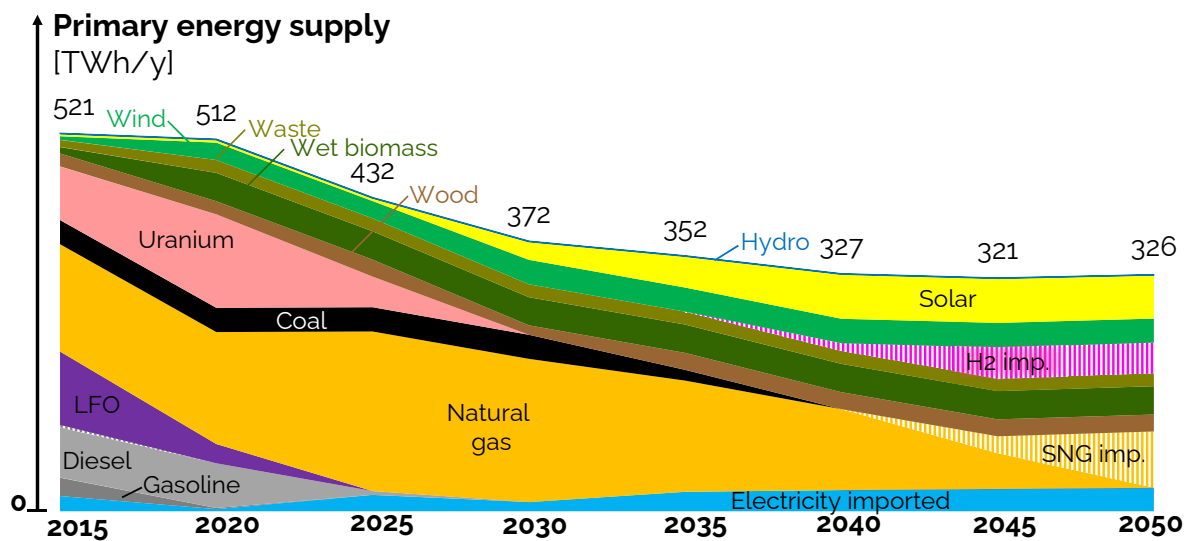


Figure 7.3 – Primary energy supply for the different years. Stripped surfaces are imported renewable fuels. Abbreviations: hydrogen (H₂), imported (imp.) and synthetic natural gas (SNG).

The first step to defossilise the system is to reduce the primary energy consumption by shifting from former technologies to more efficient ones. Despite an increasing energy demand of 23.4% between 2015 and 2050, the primary energy supplied will be reduced by 37% over the same period. The efficiency is mainly driven by an improvement in low temperature heat production and an increase of public mobility. Low temperature heat switches as much as possible from decentralised hydrocarbon based fuels to centralised heat pump systems. Later (after 2025), the decentralised heat relies on thermal heat pumps (HPs) and finally (after 2035) electrical HPs. The other major efficiency driver is the increase of public mobility use at the expense of private one. Between 2015 and 2020, 30% of the private mobility (mainly gasoline cars) is substituted by public mobility, mainly electricity based: trains, trams, metro and electric-buses.

Among all the non-renewable fuels, NG has the largest share due to its low GWP (the second after nuclear energy) and its suitability for multiple applications (electricity, heating and mobility). Coal is also kept for industrial processes (heat generation) as it is very cheap.

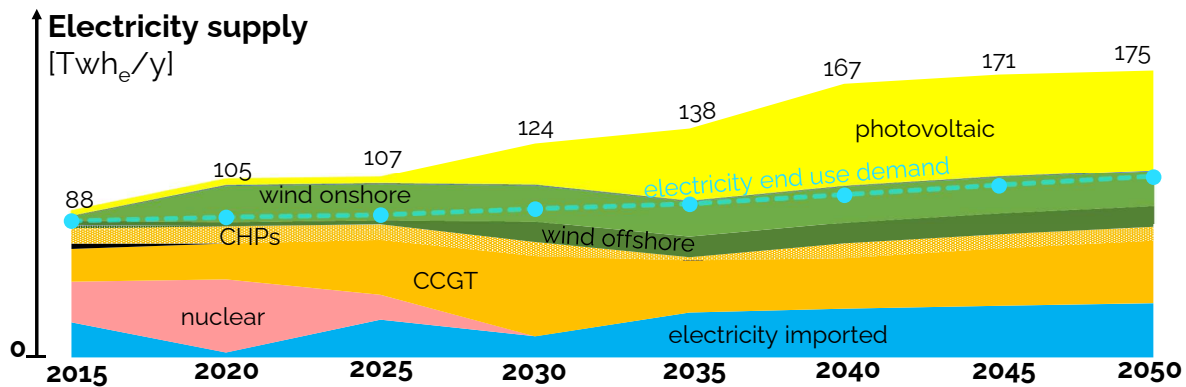


Figure 7.4 – Electricity end use demand (EUD) (in dashed blue line) and production mix over the transition. The gap between production and EUD reflects the electrification of the heat and mobility sectors. Abbreviations: combined cycle gas turbine (CCGT), cogeneration of heat and power (CHP).

The strategy to phase out nuclear

Figure 7.4 illustrates the electricity production over the transition. At first, NG implantation increases for electricity production and compensates, in the period 2015-2025, an increasing demand and the nuclear phase-out. Over the same period, even if electricity EUD remains more or less constant, the electricity demand rises from 88 TWh to 107 TWh, reflecting an electrification of the heat and the mobility sectors. NG-based technologies are offsetting the decline in nuclear production; and even more by following the growing demand. In more details, the nuclear phasing out is managed as:

- In 2020, the nuclear park is entirely available and wind onshore potential gets fully exploited. To handle intermittency, as a back-up technology, CCGTs are frequently used and their capacity factor reaches almost 58%.
- In 2025, the nuclear capacity available is 2 GW (Tihange 3 and Doel 4) resulting in a drop of 29 TWh/y. To avoid aggravating the problem, the demand for electricity doesn't grow much, staying at 107 TWh/y. To compensate the shortage, CCGTs are used at base load (capacity factor above 95%) and electricity import rises (22.6 TWh/y).
- In 2030, the nuclear park is no longer available, which results in a drop of 15 TWh/y. Combined with the increasing electricity demand (+17 TWh/y), the shortage is 32 TWh/y. To compensate, renewable are massively deployed with 20 563 MW of PV and 2 788 MW of offshore wind turbines; but also flexible gas power plants are deployed with 3 002 MW of CCGT. The latter is solicited around 80% of its time.
- After 2030, electricity demand continues to grow at a steady pace (≈ 13 TWh/5 years). To match this increase in demand, PV is massively deployed and reaches almost 60 GW, in 2040. To facilitate the integration of this later technology, additional gas-CHPs (1 257 MW_{th}) and CCGTs (2 409 MW) are installed and electricity imports increase up to the limit of ≈ 30 TWh/y (30% of electricity EUD).

The importance of electrification

On the one hand, the electricity demand almost doubles in 35 years to reach 175 TWh/y. On the other hand, the demand for electricity is increasing only modestly up to 104 TWh/y (+32%). As the energy must be balanced - thus this extra electricity must be consumed - Figure 7.5 shows how other sectors electrify. It appears that the most effective path to reduce emissions is to change the passenger mobility and the low temperature sectors.

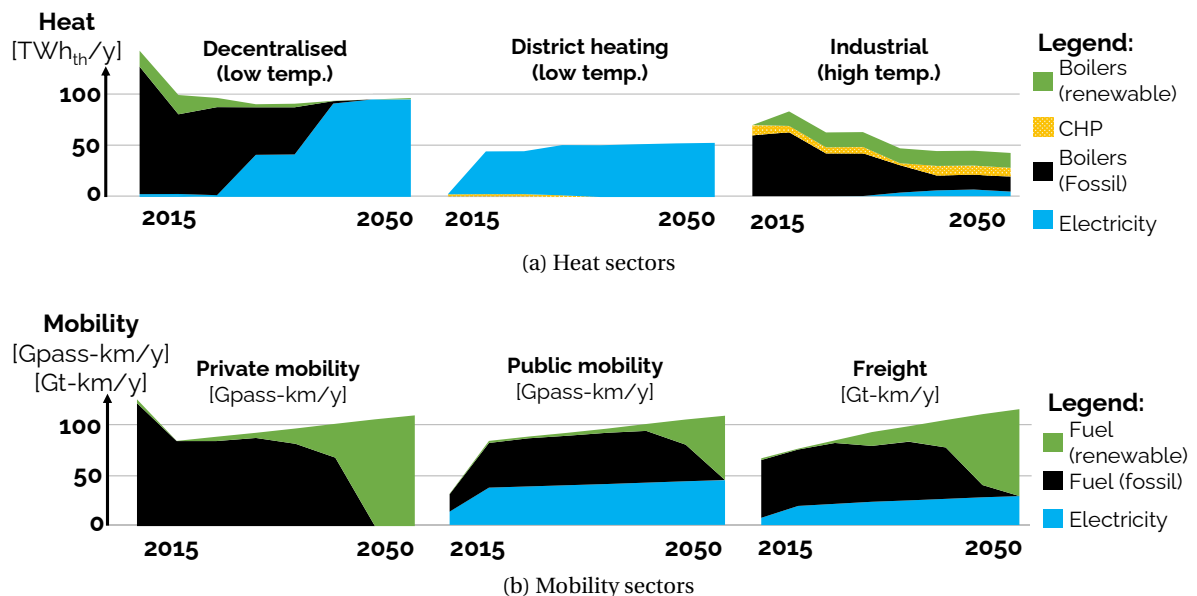


Figure 7.5 – Electrification and penetration of renewable fuels in the heat and mobility sectors. Abbreviations: cogeneration of heat and power (CHP), passenger (pass) temperature (temp.).

The majority of low-temperature heat demand is space heating. In 2015, most of the decentralised boilers are oil or gas powered. As early as in 2020, the oil boilers are decommissioned and replaced by thermal HP. The latter is powered with gas and has the advantage to not overloading the power grid in the first years of the transition¹. On the contrary, gas boilers are used until they reach their lifetime of 17 years. They are replaced by electrical HPs. Once gas powered HP reaches its expected lifetime of 20 years, it will be replaced by electrical HPs. The low temperature heat sectors become fully electrified around 2040. Switching from fossil fuel boilers to heat pumps (HPs) has the advantage to reduce the final energy consumption. In parallel to these changes, district heating networks (DHNs) replace decentralised boilers: this implies the deployment of more efficient technologies, mainly HP, and also facilitates the integration of large-scale thermal storage.

If considering electrification as the usage of electricity in a sector; thus, the industrial sector is the

¹Oil boilers are usually installed in remote area, where gas or district heating networks are not profitable. The model doesn't account for these spatial constraints and this results is debatable. Perhaps these boilers should be replaced by electrical HP.

least electrified. By extending the definition of electrification with the inclusion of sector coupling, the industrial sector plays a major role in the power system. Indeed, gas-based CHPs support the power system during winter. During summer, CHPs are turned off and boilers take over to supply the high temperature heat demand. From 2035, PV installed capacity reaches 44 GW and electrical resistors are deployed to absorb intermittent excesses. Their installed capacity initially is 3 GW (in 2035) and reaches 8 GW in 2040. Electrical resistors are a cheap technology and is used only during excesses of intermittent renewables (6-7% of the time). In addition, they can be coupled with high temperature storage to buffer the production at night.

As previously mentioned in Section 4.3.3, public mobility technologies have the advantage to be more energy efficient than individual cars. In addition, their electrification is simpler as they can use electrified infrastructures (railways, trolleys...). It results in a drastic switch from fossil private cars to electrified public vehicles (trains, trams and buses). This switch happens after 10 years, when cars reach their expected lifetime (10 years). At that time all gasoline cars and most of the diesel cars are removed. The public mobility reaches its maximum level ($\%_{public,max}$) of deployment. As a result, public mobility has both advantage to emit less emissions and to be less expensive.

As a reminder, changes in the following three sectors are limited: low temperature heat (centralised plus decentralised), passenger mobility (private plus public) and freight mobility. The default values are 33% for heat and 50% for mobility. This implies that it takes 15 years to completely transform the low temperature heat sectors and only 10 years for mobility ones. If the constraint is removed, it can be seen that some sectors would mutate more rapidly in order to withdraw some technologies which are less efficient and have a high operating cost, such as the oil boiler. The full documentation is provided in Section 3.1.2.

The role of renewable fuels

Figure 7.5 shows the substitutions of fossil fuels to renewable fuels. In the industrial heat sector, coal and gas boilers are replaced by waste and wood. A harder task is to defossilise the mobility sector. The latter lowers its GHG emissions by shifting from fossil fuels to hydrogen. Fuel cell (FC) cars are massively deployed in the period 2020-2025. Indeed, this technology is cost competitive with other cars and rely on a carbon free energy carrier: hydrogen. At first, hydrogen is produced from fossil fuels - also called *grey-hydrogen* - (methane reforming) and later replaced by renewable hydrogen (electrolysis and imports).

Figure 7.6 illustrates the origin of renewable fuels and *grey-hydrogen* (locally produced or imported) and their application (support power sector, heat or mobility).

Nowadays, renewable fuels are already produced. The two conversion pathways used are: biogas

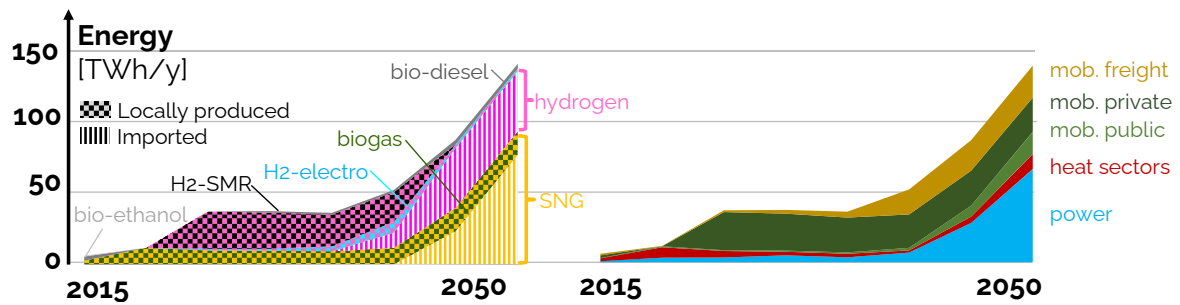


Figure 7.6 – Renewable fuels production (left) and consumption (right). RE fuels can either be locally produced (square) or imported (stripes). Abbreviations: electro (electrolyser) mobility (Mob.), steam methane reforming (SMR), synthetic natural gas (SNG).

from wet biomass and bio-ethanol². The biogas is blended in the gas sector and used in several applications, the bio-ethanol is blended with gasoline for mobility. In 2025, two other pathways are installed: methane reforming³ to produce *grey-hydrogen*; and pyrolysis to produce bio-diesel. These fuels are exclusively used for mobility. From 2035, electrolyzers start to be deployed as their investment cost is much cheaper than in 2015 and excesses of electricity produced with intermittent renewables are more recurrent. The hydrogen produced replace the *grey-hydrogen* for mobility applications. In addition, the hydrogen slightly increases as freight mobility switches to FC trucks. From 2040, renewable fuels are imported to first replace *grey-hydrogen* and then NG. NG is mostly used in CCGT and gas-CHP to produce electricity and heat. the reason why gas is still used in the production of electricity is that the intermittency of REs has still to be compensated by dispatchable technologies.

Except for biogas, which is competitive since the beginning, the other renewable fuels appear at the end of the transition to substitute fossil fuels. On the one hand, imported renewable fuels are expensive and the system delays its use. On the other hand, Belgium cannot satisfy its need with endogenous resources plus imported electricity, and renewable fuels appear as the unavoidable option to fill the gap.

7.1.3 Investment required

In the previous section, the technical aspects of the transition have been investigated. However, the pathway has been optimised on an economical criteria: the minimisation of the transition cost. In this section, the economical aspects are investigated in terms of annualised system cost (as

²In Belgium, three major actors are producing bio-ethanol: AlcobioFuel, Tereos Sytal and Biowanze. The feedstock used is crops, mainly wheat and corn. Data from: <http://www.belgianbioethanol.be/>, visited on 14-08-2020. In the model, crops are not accounted for as they compete with food and the Belgium territory is too small. Thus only imports of bio-ethanol are allowed.

³This technology is well implemented today as it produces tens of TWh/y of hydrogen for industries non energy demand.

previously used) and investment required between two representative years.

Resources expenses: a switch from fossil to renewable ones

Similarly to the Pareto results in Chapter 5, Figure 7.7 gives an overview of the expenses reported to the different years. The pathway model verifies the transition trends presented in the previous Chapter (Figure 5.3): the annualised yearly cost slightly decreases before surging. The same strategies drive the curve shape: implementing efficient technologies can both reduce the system cost and emissions; and then, to reach a low emissions society, PV is massively deployed and renewable fuels are imported.

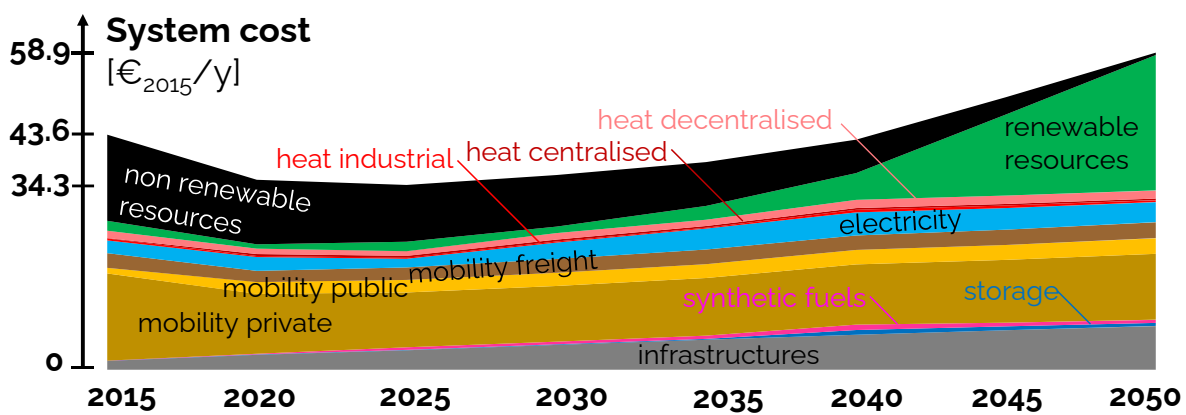


Figure 7.7 – Total annualised cost evolution for the different representative years. The costs are broken down by investments per sector, and resources.

In 2050, the imports of electricity and fuels account for 3.4 and 20.7 b€₂₀₁₅, respectively. Due to the higher cost of renewable fuels compared to their equivalent fossil one, the energy system in 2050 requires 15.2 b€₂₀₁₅ more than the one in 2015. Efficiency measures do not mitigate the increase in energy demand linked to the population growth, which is - according to the European Commission projections [89] - from 11.38 to 14.79 million between 2015 and 2050. As a result, the cost of the system per person amounts to 3 983 €₂₀₁₅ per person in 2050, which is not much different from the estimated cost of 3 836 €₂₀₁₅ per person in 2015.

Sector expenses

In the following two different costs are used: the annual system cost - the one used in the previous chapters - gives the annualised cost of technologies in a year plus its maintenance and operating costs; and the transition cost which gives the total amount of money required over the period 2015-2050. The annual system cost can be used to analyse scenarios and pathways, while the transition cost can only be used to analyse the pathway. This latter is estimated to 1 283 b€₂₀₁₅ and can be decomposed into investment (752 b€₂₀₁₅), maintenance (138 b€₂₀₁₅) and operating costs

(393 b€₂₀₁₅). In the pathway model, the capital expenses are not reported over the year. Instead, a new technology is installed during a phase and its cost is fully accounted for during this phase. Figure 7.8 illustrates the initial investment before 2015 and investments between representative years. The initial investment required to build the energy system before 2015 is estimated to be 286.6 b€₂₀₁₅. The investments between 2015 and 2050 are estimated to be 465.6 b€₂₀₁₅.

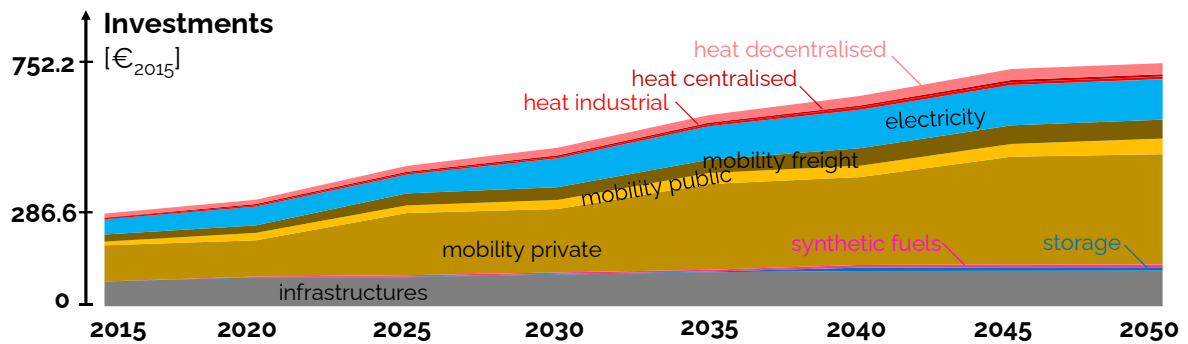


Figure 7.8 – Cumulative investments over the transition. The energy system of 2015 has an initial investment cost of 286.6 b€₂₀₁₅.

The expenses are not equally distributed among the different sectors. As the system before 2015 is imposed and consequently its investments, the following paragraphs focus on the investment after 2015, and thus over a total of 465.6 b€₂₀₁₅ (i.e. 752.2-286.6 b€₂₀₁₅). Expenses associated to new vehicles in the mobility sector alone represent 65% of the total expenses (302.5 b€₂₀₁₅). While the passenger mobility is equally distributed between the private and public mobility⁴, the capital expenses for private mobility is estimated to 229 b€₂₀₁₅⁵.

The second largest share of investments is associated to the electricity sector with a total of 77.5 b€₂₀₁₅ for production units and 21.9 b€₂₀₁₅ to reinforce the electricity grid. Onshore wind is fully deployed between 2015 and 2020 for a total investment of 10.5 b€₂₀₁₅. Between 2025 and 2040, PV is deployed with an investment around 15 b€₂₀₁₅ per phase. Between 2025 and 2030, offshore wind is fully deployed (3.5 GW) requiring an investment of 11.9 b€₂₀₁₅. After 2040, wind onshore reaches its expected lifetime, and is thus replaced by a new capacity. In addition to the RE capacity, 3.6 GW of CCGTs capacity are installed for a total cost of 3.2 b€₂₀₁₅. Finally, 21.9 b€₂₀₁₅ are required to adapt the grid in order to absorb the deployed of intermittent renewables. This major investment is spread during the renewable deployment (2015-2040).

Third is the heating sector which accounts for heat production technologies (32.6 b€₂₀₁₅), such as boilers or CHP; and heat DHN infrastructure (7.9 b€₂₀₁₅). DHN is mainly deployed between 2015

⁴The passenger mobility is constrained to cover at least 50% by private cars.

⁵One might doubt that private cars could cover almost half of the investments required during the transition. A quick calculation can comfort this result: assuming 3 million of private cars in Belgium with an average price of 20 k€₂₀₁₅, the total fleet cost would be 60 b€₂₀₁₅. Also, assuming a lifetime of 10 years, the fleet must be replaced 3 times between 2015 and 2050. It results in a total cost for private mobility of 240 b€₂₀₁₅ over the transition.

and 2020 and then slightly increased between 2025 and 2040. As previously presented in Figure 7.5, centralised heat production are mainly heat pumps (except the installed capacity before 2015) and represent an investment of 6.2 b€₂₀₁₅. The decentralised sector decommissioned boilers, oil and gas, in the periods 2015-2025. These boilers are replaced by connecting the dwellings to the DHN or installing a gas HP. Decentralised heat is also supplied by wood, gas boilers and other technologies more sporadically. Once these technologies reach their expected lifetime, they are replaced by electrical HPs. 4.7 b€₂₀₁₅ are spent in the industrial heating sector: 1.3 b€₂₀₁₅ for 1.3 GW_{th} of gas CHP, 2.1 b€₂₀₁₅ for 8.6 GW_{th} of electrical resistors and the rest in back-up boilers. Industrial sector plays a key role to facilitate the integration of intermittent renewables: the lack of productions are backed-up by gas CHPs, or during a production excess, electrical resistors are turned on to consume gigawatts of power.

In fourth to sixth places, we find the storage (10.3 b€₂₀₁₅), synthetic fuels production (8.5 b€₂₀₁₅) and efficiency measures (4.4 b€₂₀₁₅)⁶, respectively. Before 2035, the following storage are installed by order of capacity: thermal (low (2 060 GWh) and high temperature (0.3 GWh)), pumped hydro storage (0.6 GWh⁷), hydrogen (16.5 GWh) and SLF (95.3 GWh). After 2035, the PV capacity reaches its maximum of 59 GW, this result in a need of daily storage that 30.9 GWh batteries will partially answer (6.2 b€₂₀₁₅). Over the same period, the synthetic fuels production experience a peak of investment of 3.3 b€₂₀₁₅ to replace the former anaerobic digestion reactors by hydrolysis ones. The latter has a better efficiency, at a higher cost. Surprisingly, investments in storage technologies represent 2% (10.3 b€₂₀₁₅ out of 465.6 b€₂₀₁₅), and half is for batteries (6.2 b€₂₀₁₅) followed by thermal storage (4.1 b€₂₀₁₅).

A limitation of the model is to not account for the period after 2050. Thus, ones could argue that massive investments will be required in the following period (2050_2055) to renovate technologies which will reach their lifetime. By applying the same methodology presented in Chapter 3 (see Eqs (3.1), (3.4) and (3.10)), the investments in 2050_2055 are estimated to 75.8 b€₂₀₁₅. This is in line with the investment performed during each phase, which are between 18.1 and 104.4 b€₂₀₁₅ with an average of 66.7b€₂₀₁₅.

Merit order

Through the transition, a merit order emerges. Figure 7.9 gives an illustrative road-map for the transition based on the previous results and explained hereafter. At first (2015-2025), onshore wind is fully deployed and the electricity production exceeds the electricity demand. Thus, electrification of other sectors starts, especially centralised HP with the massive deployment of DHN and the electrification of public mobility. In addition, the heat and mobility sectors switch on centralised

⁶The efficiency measures are estimated to be 5.6 b€₂₀₁₅. The difference reflects the interest rate over the transition.

⁷There is already a capacity installed in 2015. The 0.6 GWh represents extra capacity.

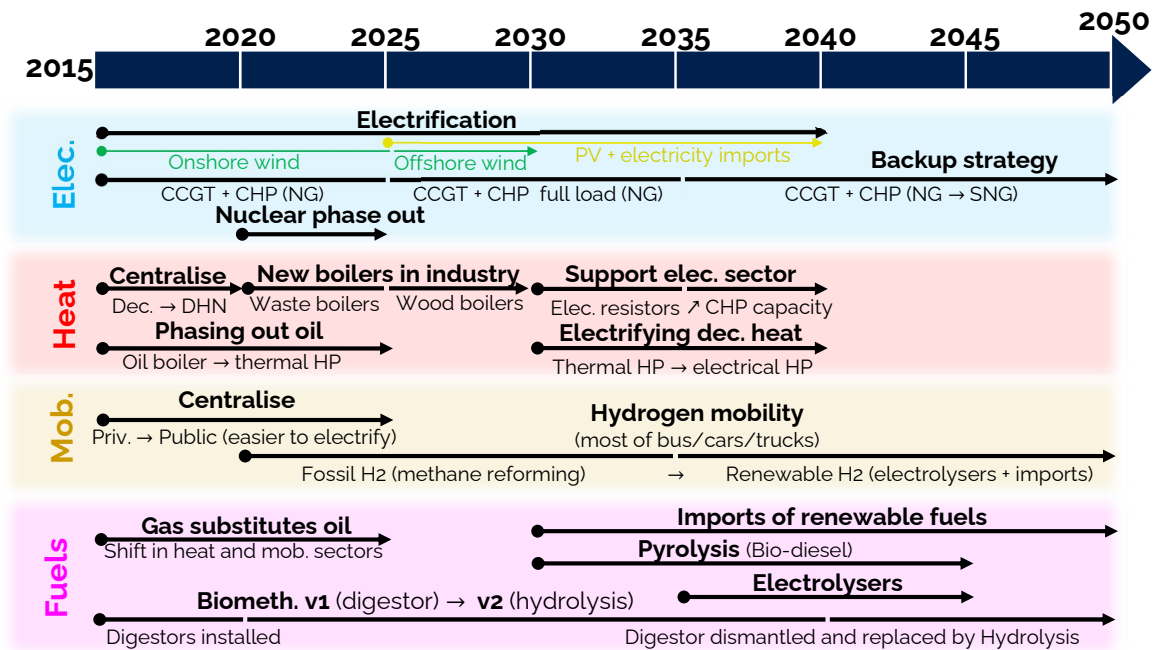


Figure 7.9 – Illustrative road-map for the energy transition. a gap in an arrow indicates that the technologies (indicated below) are installed at different times, e.g. hydrogen mobility uses first fossil H₂ and then (after 2035) renewable hydrogen. Abbreviations: combined cycle gas turbine (CCGT), cogeneration of heat and power (CHP), decentralised heat (dec.), district heating network (DHN), electricity (elec.), heat pump (HP), hydrogen (H₂), mobility (mob.), photovoltaic (PV) and version 1 (v1).

technologies (DHN and public mobility). In the gas sector wet biomass is transformed into gas with a biomethanisation process and extra gas is used for public mobility (coaches and buses) and freight (barges). Second (2020-2040), PV and hydrogen technologies are deployed. On the one hand, PV starts a progressive growth of 15 GW per phase. On the other hand, methane is converted into hydrogen which is later used for private mobility. As previously mentioned, cars have an expected lifetime of 10 years, thus, between 2020 and 2025, the fleet is renewed. FC vehicles are more competitive from an efficiency point of view, despite the higher cost, hence they are deployed. In 2025, all the hydrogen produced is based on fossil resources. Third (2025-2035), intermittent renewables continue to be deployed and offshore wind reaches its full deployment. Due to this rising intermittent power production capacity, a need of flexibility is required. To back-up the production, extra CCGT and CHP capacities are installed. To absorb excess of production, electrification of heat behaves as a flexible consumer. This involves HPs coupled with thermal storage and industrial electric resistors coupled with high temperature thermal storage. Fourth (2030-2040), PV reaches its maximum of 59.2 GW and requires more flexible capacities: electrolyzers and then batteries are deployed. In parallel, the mobility sectors starts to defossilise: hydrogen is produced based on renewable resources and then used for private and freight mobility. In addition, biomass is processed into diesel, later used in diesel trucks. Finally, the biomethanisation capacities installed in 2015-2020 reach its expected lifetime and is replaced by a more efficient but more expensive technology: bio-hydrolysis. Fifth (2035-2050), renewable capacities have reached their maximum potential. Thus, the model uses imported renewable fuels to phase out fossil fuels in its mix, such as SNG which replaces NG.

7.2 Comparison to other pathways

The results of the previous section may seem meaningless as we have little concrete values with which to compare them. To improve the analysis of the reference case study, it would be worth to compare its results to other pathways. This approach will allow to answer questions, such as: is the total cost of the system increasing around 2050 because of defossilisation or because of the increasing end-use demand? To answer this question, two non-CO₂ constrained pathways have been analysed on the same period: a '*business-as-usual*' (BAU) and a '*cost-optimum*' (OPT). Both pathways don't have any restriction on the emissions they produce during the representative years and over the periods. To implement these pathways, the maximum yearly CO₂ emissions (gwp_{limit}) are relaxed. In addition, as the *business-as-usual* pathway is non optimal, additional constraints are added and some parameters are changed to the model to force the 2015 configuration:

- the shares of public mobility (%**Public**), train and boat in freight (%**Freight**) and centralised heat production (%**DHN**) are those from 2015;
- the shares of technologies are fixed. As an example, in 2015 the amount of private mobility supplied by gasoline car was 35%. Thus this technology has to supply the same share over the

transition.

- the nuclear power plants are not decommissioned
- the electricity imported is fixed at 10% of the electricity EUD.
- the shares of biofuels and biogas imported are those of 2015.

Once the comparison performed, an additional scenario will be presented. In this scenario, called **Inaction**, the transition is delayed by 5 years. Table 7.1 summarises the results in terms of total transition cost and GHG emissions. In addition, changes in energy strategy is enumerated and extended in the following paragraphs.

Table 7.1 – Transition cost and emissions comparison between the reference scenario (**Reference**) and three additional scenarios: business-as-usual (**BAU**), cost-optimum without CO₂ constraint (**OPT**), transition starts in 2020 (**Inaction**). The difference is calculated based on the **Reference** case (Δ). **Strategy** summarises the system design difference compared to the reference scenario. Abbreviation: natural gas (NG) and renewable energy (RE).

	Total cost		Total emissions		Strategy
	[b€ ₂₀₁₅]	Δ	[MtCO ₂]	Δ	
Reference	1 283	-	2 238	-	-
BAU	1 627	344	4 628	2 391	system similar to the one in 2015
OPT	1 197	-86	3 932	1 694	no RE fuels and NG dominates
Inaction	1 340	57	2 440	202	doubled efforts after the delayed years

7.2.1 Comparison with a business as usual pathway

Figure 7.10 shows the emission differences between the *business-as-usual* pathway and the reference one. Unsurprisingly, emissions in the first pathway remain relatively constant. The exception is in 2020, where the full availability of nuclear power plants decreases slightly the emissions. Indeed, the emissions related to electricity production are reduced by 11 MtCO₂/y. After, the emissions remain more or less stable.

The comparison of both pathways are depicted in terms of emissions in Figure 7.10. Four categories are identified: (i) use of local renewables, (ii) use of imported renewable fuels, (iii) use of imported electricity and (iv) use of efficient technologies. As both pathway emissions cannot be compared directly, these categories were computed by assuming reference emission intensities. We deem *emission intensity* as the GHG emissions produced to obtain 1 unit of final energy. As an example, the emission intensity of electricity imported is the one of the European mix in 2015 (482 kgCO_{2eq}/MWh_e), or the emission intensity of local electricity production is the one of electricity produced by CCGTs (448 kgCO_{2eq}/MWh_e in 2015 and 412 kgCO_{2eq}/MWh_e in 2050). Based on these emissions, the savings can be computed as explained hereafter. Local renewable (i) accounts for biomass and others that produce electricity (wind, solar and hydro). The emissions saved by using

biomass are calculated based on the emission intensity of non-RE waste. And the emissions saved by using electricity from PV, wind turbines and hydro power plants are calculated based on the emission intensity of electricity produced by CCGT. The emissions saved when using imported renewable fuels (ii) are the one of their equivalent fossil fuel: gasoline for bio-gasoline, diesel for bio-diesel, NG for SNG and LFO for SLF. For the case of hydrogen, the emission intensity steam reforming of fossil NG are used ($\approx 363 \text{ kgCO}_{2\text{eq.}}/\text{MWh}_{\text{H}_2}$). The emission intensity of electricity imported (iii) is expected to reduce linearly and reach 0 in 2050 (see Section 4.1.2). The emissions saved by importing electricity is equal to the amount of electricity imported multiplied by the difference of carbon intensity between the *business-as-usual* pathway and that of the year. As an example, the emission intensity of electricity in 2035 is $206 \text{ kgCO}_{2\text{eq.}}$ per MWh, thus each MWh imported saves $482 - 206 = 276 \text{ kgCO}_{2\text{eq.}}$ per MWh (482 being the emission intensity of electricity imported in 2015 and the one for all years of the *business-as-usual* pathway). More efficient technologies (iv) allows to save primary energy and thus reduce emissions. Its emissions savings are assumed to fill the gap.

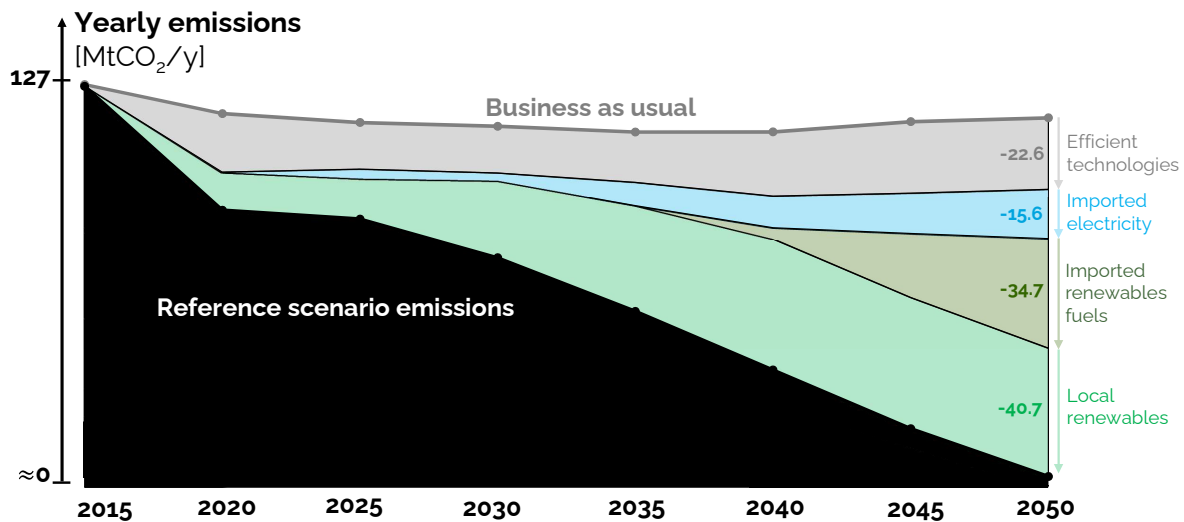


Figure 7.10 – Greenhouse gas emissions comparison between the reference scenario and a *business-as-usual* one. Negative values (on the right) show the emission difference between the business-as-usual and the reference scenarios.

Figure 7.10 corroborates previous analyses where the use of local renewables and the use of efficient technologies are the first two categories employed to reduce GHG emissions. Then, a combination of imported electricity and full deployment of local renewable potential brings the system up to its target in 2040. Finally, it is verified that the import of renewable fuels enables the system to reach carbon neutrality. Each category contributes significantly to defossilisation. More precisely, in 2050, the integration of local renewable energy allows a reduction of $40.7 \text{ MtCO}_2/\text{y}$, the import of renewable fuels of $34.7 \text{ MtCO}_2/\text{y}$, the use of efficient technologies of $22.6 \text{ MtCO}_2/\text{y}$, and finally, the import of electricity contributes to reduce the remaining $15.6 \text{ MtCO}_2/\text{y}$.

In the following, it is assumed that the comparison is between the reference solution and the

business-as-usual pathway. At first stage of the transition, more efficient technologies - mainly public mobility and centralised HP - and the use of wind turbines reduce the emissions. Then, the use of local renewables lead the reduction of emissions, followed by importing renewable fuels at low emissions. In addition, imported electricity is a source of defossilisation starting from 2025.

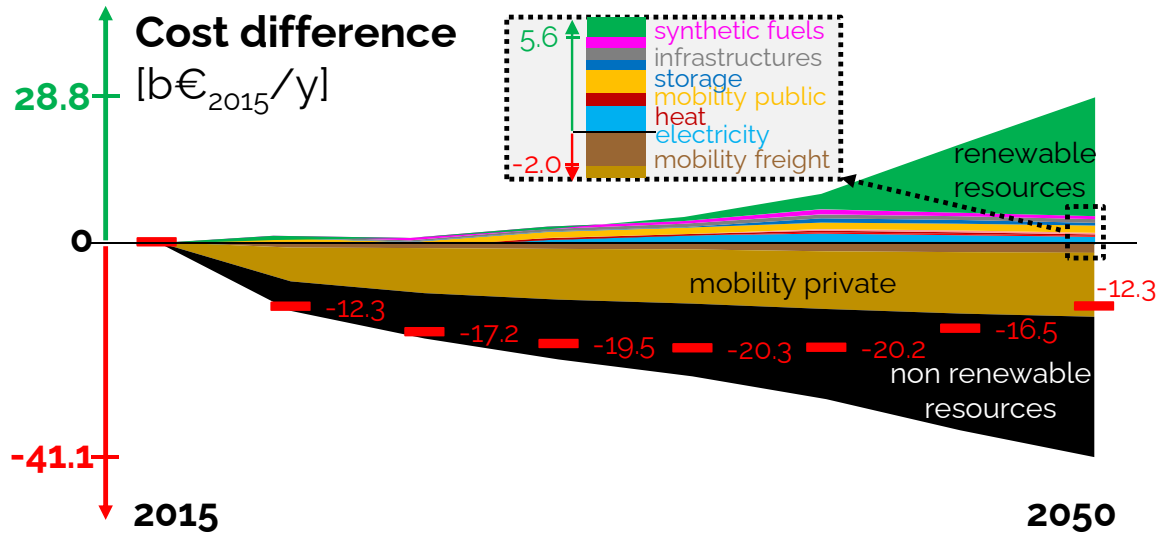


Figure 7.11 – Total annualised cost difference between the *business-as-usual* and the reference solution. Values represent additional expenses for the reference solution (positive) or *business-as-usual* solution (negative). Overall, the *business-as-usual* is more expensive than the reference solution (red dash). A zoom in is proposed in the dotted box for 2050.

In terms of cost difference, Figure 7.11 shows their balance between the two pathways. On the one hand, the *business-as-usual* pathway makes greater expenses in the private mobility sector and the purchase of fossil resources. On the other hand, the reference pathway imports expensive renewable fuels and invest more in the other sectors, mainly the public mobility and electricity ones. All-in-all, the business as usual solution is significantly more expensive than the reference one.

Another finding can be depicted when analysing in Figure 7.11 the expenses in fuels. Even if the prices of renewable fuels are greater, the expenses made for resources in the *business-as-usual* pathway are more important than the ones of the reference scenario. Thus, it means that the amount of fuels imported are much higher in the *business-as-usual* pathway (≈ 500 TWh/y) compared to the reference one (≈ 120 TWh/y).

7.2.2 Comparison with a no constrained pathway

Based on the previous paragraphs, ones could conclude that making a carbon-neutrality transition is more affordable than keeping an energy system similar to the one of today. This statement is too simplistic as the energy system in 2015 is constrained to be non-optimum. To nuance the results,

the cost-optimum pathway (**OPT**) without limitation on the CO₂ emissions will be compared to the others.

Figures 7.12 (a) and (b) shows the emissions and cost, respectively for three pathways: the reference pathway (**REF**), the *business-as-usual* pathway (**BAU**) and the cost-optimum pathway (**OPT**).

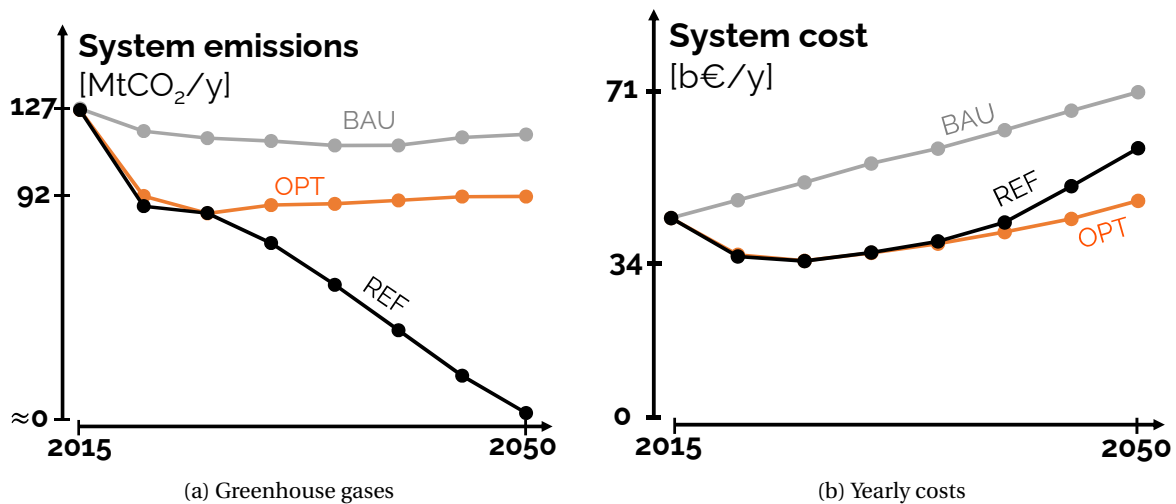


Figure 7.12 – Greenhouse gas and total annualised cost comparison between the reference pathway (**REF**), business-as-usual pathway (**BAU**) and cost-optimum pathway (**OPT**).

As expected, compared to the reference pathway, the cost-optimum one has a lower system cost and greater emissions. Both pathways follow the same trends at the beginning of the transition: deploying wind turbines, moving to public mobility and using hydrogen for private cars. After, most of the technologies in the cost-optimum pathway continue using fossil NG which explains a plateau for the emissions. This system has a similar cost than the reference pathway until renewable fuels substitute fossil ones (≥ 2035).

The cost difference is illustrated in Figure 7.13 for the cost-optimum and the reference pathways. On the one hand, the cost-optimum pathway has greater expenses for fossil fuels and the freight sector. On the other hand, the reference pathway imports renewable fuels and has greater expenses in all other sectors. These additional expenses in sector represents the greater penetration of PV and its integration cost, such as reinforcement of the power grid, storage, electrification of high temperature heat sector, etc. The reference solution become more expensive at low emissions, mainly due to the greater cost of renewable fuels compare to the similar fossil ones.

In terms of transition cost, the reference solution (1 283 b€₂₀₁₅) is only 7% more expensive than the cost-optimum solution (1 197 b€₂₀₁₅) while it is 21% cheaper than the *business-as-usual* solution (1 627 b€₂₀₁₅).

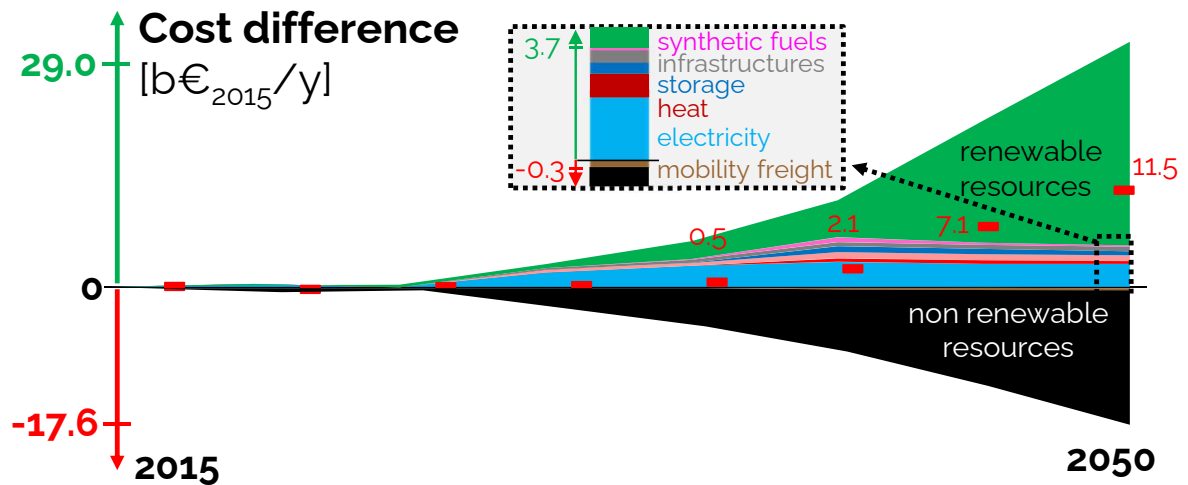


Figure 7.13 – Total annualised cost comparison between the *cost-optimum* without CO₂ constraint and the reference scenario. Values represent additional expenses for the reference solution (positive) or *business-as-usual* solution (negative). Overall, the reference solution is more expensive than the other one (red dash). A zoom in is proposed in the dotted box for 2050.

7.2.3 What is the impact of inaction?

Setting an energy governance for the next decades is a long process that needs several years to be analysed and accepted by the parliaments and governments. Unfortunately, these lost years are precious and would allow for a smoother transition. Perhaps the transition cost and emissions could both be reduced. To assess the cost of waiting, the following pathway will be investigated. In this pathway, the transition starts in 2025, and 2020 is forced to be a *business-as-usual* year.

In this delayed pathway, both cost and emissions are greater than in the reference one. Cost is 1 340 b€ (+57 b€) and emissions are 2.43 GtCO₂ (+0.202 GtCO₂). These increase are mainly related to the use of oil in decentralised heating and private cars. Thus, waiting appears as a non profitable option both in terms of cost and greenhouse gas emissions. What if Belgium was constrained to a given carbon budget? To answer this question, the same pathway has been computed with a limit on the total GHG emissions equivalent to the one of the reference pathway. In this case, the cost is 69 b€₂₀₁₅ more expensive than the reference solution.

On the way to carbon neutrality, the first measures taken from 2020 to 2035 can be both beneficial in terms of emissions and cost. Regarding the carbon budget allowed for Belgium, the years of inaction are the ones we will regret the most at the end of the race.

7.2.4 Comparison with other studies

This methodology is intrinsically impossible to validate. However, the results can be compared with other similar studies. In particular, two studies have been identified. The Federal Planning Bureau (FBP) with two regional institution analysed, in 2013, five transition pathway scenarios up to 2050 [101], this study will later be called **FBP**. The Climate Change Service of the Federal Public Service Health launched an initiative in 2012 entitled '*Low Carbon Belgium by 2050*'. This initiative resulted in a report and a calculator in 2013 [147], similarly to the first version of EnergyScope published in 2013 (see www.energyscope.ch) [149]. The Belgian calculator has since been improved into a recent expert version [148], later be called **My2050**.

In their study, The FBP compared five defossilisation scenarios with a reference one. According to their description, the latter scenario '*does not aim at forecasting the most likely evolution of the energy system, it rather serves as a benchmark to evaluate the cost of implementing the 100%*'. Thus, this scenario can be compared to the **OPT** scenario defined in this work, where there are no restrictions on the GHG emissions. The other five scenarios are based on extreme options in terms of demand reduction, electricity import, biomass import, PV deployment, and Wind deployment. Similar to section 5.4, each of these scenarios extends a technology on which the solution will strongly rely. To compare their results with ours, the key performance of the five scenarios will be averaged.

In the calculator (**My2050**), the user can play with cursors to define his own scenario. He then decides on the penetration of electric vehicles, renewables, demand reduction, etc. In the current version (consulted on 09-02-2021), six pre-programmed scenarios are proposed. A reference scenario is defined without GHG constraints after 2020 and with a mix of solutions similar to what exists today. This scenario can be compared with the business-as-usual (BAU) scenario of our study. Three scenarios are partially based on demand reduction: a strong change in lifestyle (CORE), a profound change in behaviour with a strong decrease in demand (behavior), an intense emissions reduction including a decrease in demand (-95GHG). As this option is not implemented in our model, these scenarios won't be accounted for. It remains two scenarios: one based on an optimistic evolution of technologies and (Technology), and one focusing on an increased dependence on neighbouring countries (EU integration). These two will be compared to our solutions.

Table 7.2 compares the consumption of primary energy and electricity for the different transition scenarios, in 2050. In terms of primary energy and electricity, the two studies have a wide range of values reflecting the difference in resources used between scenarios. The values obtained with our model are within the ranges, except for electricity, where the study conducted by the **FBP** estimates a minimum electrification of 5 TWh/y more important than our result.

Table 7.3 shows the total annualised costs for the different scenarios in 2050. The costs are shown in terms of annualised cost and difference from the study's reference scenario. Compared to My2050, the BAU and reference scenarios are consistent. Compared to FBP, only the difference between the

7.2. Comparison to other pathways

Table 7.2 – Comparison of the pathway results with the literature in terms of Primary energy demand and electricity production, in 2050.

Scenarios	FPB [101]	My2050 [148]	EnergyScope Pathway
Primary energy [TWh]	305-417 ^a	307-364 ^b	326
Electricity production [TWh _e]	180-310 ^a	126-140 ^b	175

^aThe wide range comes from the different types of resources used. For primary energy, the lower limit corresponds to scenarios with reduced demand or electricity imports from neighbouring countries, the upper limit corresponds to scenarios with biomass, wind and PV. The trends are the same for electricity production, except for the biomass scenario where most of it is used directly for heating.

^b The *Technology* scenario uses 364 TWh/y of primary energy and produce/import 126 TWh/y of electricity. The other values are for the *EU integration* scenario.

Table 7.3 – Comparison of the pathway results with the literature in terms of annualised system cost, in 2050. Some data were not found (blank).

Scenarios	FPB [101]	My2050 [148]	EnergyScope Pathway
Optimal scenario			47.5
Business-as-usual		73 ^a	71.2 (+24)
Reference	(+16.1) ^b	63-82 ^c	58.9 (+11.5)

^aBased on the 'Reference' scenario.

^bAveraged value for the five scenarios of data in the 'Total additional energy system cost' (Table 19). An inflation of 1.19% as been used to convert €₂₀₀₅ in €₂₀₁₅.

^cRespectively for *Technology* and *EU integration* scenarios.

reference and OPT solution can be compared, and there is a difference of 4.5 b€₂₀₁₅/y. The results are therefore of the same order of magnitude with differences of up to 10-15 %.

The study performed by the **FBP** gives more detailed information. As an example, the cost for importing resources between 17.3 and 19.4 b€₂₀₁₅⁸ for scenarios where renewable fuels and fossils fuels are imported, respectively [101]. In these scenarios, from 1.2 to up to 8.3 b€₂₀₁₅ are used for importing electricity. These results are in line with our estimation, 20.7 for fuels and 3.4 b€₂₀₁₅ for electricity (see Section 7.1.3).

In their work, Devogelaer et al. [101] states ‘*The biggest investments, both in the reference scenario as in the renewable scenarios, have to be made in the transport system. Investments needed include mainly material assets amongst which the alternatively propelled (including hydrogen) transport means. Next to investments in the transport sector, power generation investments are the largest and eat up around a quarter of all investments to be made in the energy system for the 100% renewable energy future*’. These trends are verified in the EnergyScope Pathway results. Devogelaer et al. [101] estimates the cumulative investment expenditures for the transport sector around 600 b€₂₀₀₅ over the period 2013-2050. This estimation, which is the same for all the different scenarios, is greater than the 414 b€₂₀₁₅⁹ estimated by our model. Three difference of hypothesis can motivate the difference: the share of private mobility, the price of vehicles and the infrastructure cost for transport that is partially taken in their work.

The studies are not based on the same assumptions, do not use the same data, do not include the sectors in the same way. A whole series of reasons why results may diverge. In the previous paragraphs, the orders of magnitude were compared and show that results of the three studies are consistent.

7.3 Impact of political decisions and uncertain parameters

The EnergyScope Pathway methodology required additional parameters which haven't been investigated in the previous chapter: the maximum amount of GHG emissions during the transition, and a set of parameters representing the society inertia (see Section 3.1.2). To mitigate climate change, what really matters are not the yearly emissions but the overall greenhouse gas emitted until the country reaches its carbon neutrality. Maybe, the country can halved its carbon budget with a little financial effort. The second parameter avoids unrealistic changes in the system (i.e. society inertia). As a reminder, these parameters limit the amount of change in a sector, between two representative years. More specifically, they limit the rate at which technologies are changed for low temperature heat ($lim_{LT,ren}$), Eq. (3.15), passenger mobility ($lim_{MobPass}$), Eq. (3.16) and freight

⁸Data of Figure 21 from [101] are expressed in €₂₀₀₅. The real inflation rate of 1.19 has been used over the period, which is equivalent to an average rate of 1.77% per year in line with the interest rate in the model.

⁹112 b€ of initial investment, plus 302 of investment during the transition.

mobility ($lim_{MobFreight}$), Eq. (3.17). Thus, a change in these values can drastically change the system.

Complementary to this arbitrary parameters, other parameters are uncertain. In Chapter 6, out of 122 parameters investigated, only a few of them were driving the uncertainty on the annual system cost, such as renewable fuel prices, nuclear capacity allowed or fuel cells prices and efficiencies. These latter accounts for most of the uncertainty, the impact of their uncertainty will be analysed in the following section.

To shed light on these issues, the pathway will be optimised for a different set of values for each parameters. The carbon budget will start from the reference solution, where a total of 2.238 GtCO₂ were emitted over the transition, and finish to the lowest emissions the system can achieve. Similarly, to analyse the society inertia, results for different values of the parameters will be investigated. Starting from no inertia (parameters equal to one) to the strongest inertia which still allows a transition. For uncertain parameters, pathways with extreme values of parameters and the reference one will be compared in terms of cost, emissions and investment strategies.

7.3.1 The influence of the carbon budget

In the reference pathway, 2.24 GtCO₂ were emitted during the transition. Worldwide, the IPCC estimates the carbon budget to be between 420 and 1 170 GtCO₂ if we were to stay below the 1.5°C and 2°C thresholds, respectively [150]. In other words, with the target of 1.5°C, the reference pathway results requires 0.5% of the world's emissions for 0.14% of its population. Thus, the reference pathway emits more than the quota per capita. Perhaps by limiting the emissions budget, the total cost of the system will be little affected.

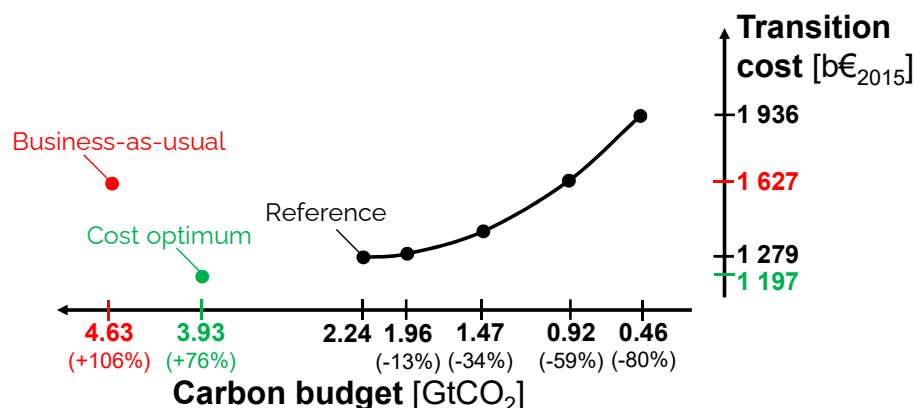


Figure 7.14 – Total transition cost for different carbon budget (black dots). The results are compared with two additional scenarios where GHG emissions are not limited: the cost optimum (green), and the business-as-usual (red). The relative emission differences are given (in brackets) compared to the reference case.

Figure 7.14 shows the impact of constraining the emissions budget on the total transition cost. Starting from the reference pathway (2.24 GtCO₂), the system can achieve a transition with a limited budget of 0.46 GtCO₂ at the expense of its cost. Between these two extremes, different pathways have been investigated. the shape of the curve is quadratic showing that it is possible to reduce emissions slightly without having too much impact on the cost. In fact, reducing emissions by 13% would cost 1.3% more, which represents 60 € per ton of CO₂ saved. Reducing further would imply a cost per ton of 157 (-34%), 269 (-59%) and 368 (-80%) €/tCO₂.

7.3.2 Changing the behaviour

The society inertia has been represented by a limit on the amount of technologies changing in a sector between two representative years. It represents the aversion of citizens to change, the lack of manpower to install new technologies, a limit on the production of a technology, or a mix of these three. Figures 7.15a and 7.15b show the impact of a change in these parameters on the transition cost and emissions, respectively. The x-axis represents the number of years required to fully change a sector. It starts at the minimum, which is the duration of a phase (i.e. 5 years).

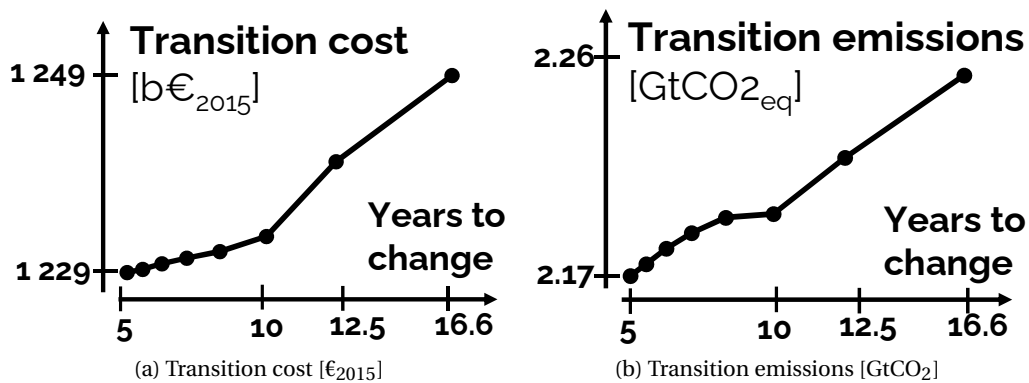


Figure 7.15 – Total transition cost for different society inertia. The more flexible the society, the lower the cost and emissions. 5 years mean that all sector can be changed during between two representative years.

Results show that inertia is critical as it can result in more GHG emissions for the energy transition and at a greater cost. There is a bending point at 10 years where the cost and emissions increase drastically. Above this point the non-efficient technologies reach their lifetime and are not replaced by more efficient ones. Indeed, by re-installing a less efficient technology, the system consumes more resources and will have to decommission prematurely this technology before its expected lifetime in order to reach carbon neutrality in 2050. As an example, decentralised gas boilers are preferred over oil boilers as their fuel is cheaper. Re-installing oil boilers will lead to the premature dismantling of this technology around 2040, when oil will no longer be burned for heating and

equivalent renewable fuels will be much more expensive.

When stepping back, one will figure out that a technology installed in 2015 with an expected lifetime of 20 years will have to be replaced only once during the energy transition. This results can be translated as a political guidance: to avoid unnecessary expenses and extra emissions, only technologies compatible with carbon neutrality should be authorised in the coming years.

7.3.3 Uncertain parameters

In Chapter 6, the global sensitivity analysis listed the uncertain parameters that influence the total cost of the system. In particular, two family of resources and three types of technologies: (i) the price of hydrocarbons, (ii) the price of light renewable fuels, (iii) the cost of private vehicles, (iv) the price and efficiency of fuel cells (FCs) and (v) the nuclear capacity. Hydrocarbons prices and private vehicles costs (i and iii) have a strong impact on the system cost, but little influence on energy strategy (i.e. technologies deployed). Fossil hydrocarbons are always cheaper than their renewable equivalents, and the same is true for private mobility vehicles compared to public mobility vehicles. On the contrary, the remaining three families of parameters (ii, iv and v) will influence decision-making.

In the following paragraphs, the impact of the three latter on the energy strategy will be assessed. To do this, for each family, we will compare the reference scenario with two new scenarios where the value of the parameters is increased or decreased. In order to obtain nuanced results, the extreme values of the uncertainty ranges are taken for the price of light renewable fuels (-47.3% and +89.9%), and the price (-39.6% and +39.6%) and efficiency (-28.7% and +28.7%) of fuel cells. For nuclear capacity, we assume that only 2 reactors (Tihange 3 and Doel 4) can be extended, i.e. a total of 2 GW electricity.

Table 7.4 summarises the results in terms of total transition cost and GHG emissions. In addition, the changes in energy strategy is enumerated and extended in the following paragraphs.

Fuel cell technology

Changing the costs and efficiencies of fuel cells will have an impact on the sector where hydrogen is used (i.e. mobility), but not only. In the optimistic case, by 2025, trucks and cars will be running on hydrogen. And from 2030 to 2040, buses are gradually being converted to hydrogen. There is also a major change in the decentralised low temperature heat sector: heat pump shares the market with decentralised FC. The latter allows the cogeneration of heat and power (CHP) at a house scale. First, these technologies use NG, then once SNG and hydrogen are imported, it switches to both resources. These technologies allow the cogeneration in a flexible way. In regard to the number of units installed (15.6 GW of electrical output in 2050), decentralised power generation replaces,

Chapter 7. Energy transition pathway analysis

Table 7.4 – Transition cost and emissions comparison between the reference scenario (**Reference**) and others with uncertainties. The difference is calculated based on the **Reference** case (Δ). Optimistic means for FC cheaper and more efficient, and for RE fuels just cheaper. Pessimistic mean the opposite. **Strategy** summarises the system design difference compared to the reference scenario. Abbreviation: electricity (elec.), fuel cell (FC), renewable energy (RE) and technologies (tech.).

		Total cost		Total emissions		Strategy
		[b€ ₂₀₁₅]	Δ	[MtCO ₂]	Δ	
Reference		1 283	0	2 238	0	-
Nuclear (2 GW_{elec.})		1 254	29	2 229	8	Less NG for elec. production
FC	Optimistic	1 127	156	2 189	49	Decentralised FC CHP
	Pessimistic	1 334	-51	2 204	34	Mobility powered by gas and diesel
RE fuels	Optimistic	1 235	48	2 253	-16	More imports and less efficient tech.
	Pessimistic	1 329	-46	2 212	25	Less imports and more efficient tech.

between 2035 and 2040, the production of CCGTs and industrial gas-CHP. But also a part of the PV production which is only installed up to 88% of its potential. This change in energy strategy results in a reduced consumption of renewable fuels and consequently a reduction in the system cost.

In the pessimistic case, i.e. where the technology would be more expensive, the hydrogen sector is not developed. That means that there is neither production of hydrogen from NG (i.e. through steam methane reforming), nor imports of hydrogen. Consequently, trucks and buses run on gas and diesel, and private cars run on gasoline. The reason for the latter choice is that hybrid electric vehicle car is the most efficient engine and has an investment cost similar to internal combustion engine cars.

Uncertainty about this technology leads to very different choices which impact all sectors. Reducing this uncertainty is essential to facilitate long-term decision making, such as the establishment of a legislative framework that promotes the market development.

Renewable fuels

Varying the price of renewable fuels will impact the amount of imports and the energy strategy of the system. When prices rise (+89.9%), the system is still constrained to import renewable fuels in order to reach carbon-neutrality. Nevertheless, it prefers to import bio-diesel at a higher price than SNG as its utilisation in technologies is more efficient, resulting in a reduced import of 12.3 TWh in 2050. On the contrary, if the price is lower, hydrogen and SNG will be imported earlier and in larger quantities. These resources are used to substitute diesel in mobility and reduce the installation of PV. The resulting lack of electricity production will be compensated by CCGTs running on SNG. Indeed, installing more than 30 GW of PV implies a significant integration cost for the system.

A strong correlation is identified between the price of resources and efficient technologies. The higher the price of resources, the more efficient technologies must be deployed to limit the quantity imported and thereby reduce the import cost.

Extending nuclear energy

Keeping 2 nuclear reactors, equivalent to 2 GW of available base-load electrical power 85% of the time, allows to produce 371 TWh of electricity over the period 2026-2050. The total electricity production is almost the same than the in the reference case, with a slight overproduction of 0.6 TWh/y. This overproduction counterbalances the increased curtailment (+0.5 TWh/y) due to the non-flexibility of the implemented reactors¹⁰. In the reference scenario, the difference in power is mainly compensated by the CCGTs and gas CHPs. This implies emissions of 91.7 Mtons of GHG. With the 2 additional reactors, the system is more easily reaching its emissions target. And therefore, it will use the remaining emission quota to use more fossil energy in other sectors. In particular, gas is being used in greater quantities and for longer during the transition. It is mainly used in thermal HPs for the production of low temperature decentralised heat. This technology substitutes until 2040 the electrical heat pumps, and temporises the deployment of DHNs. The gas is also used longer in the production of hydrogen (i.e. through steam methane reformings (SMRs)) and retards the implementation of electrolyzers.

Discussion

The *EnergyScope pathway* model has been applied successfully to represent how the energy system could be defossilised. The trends towards a carbon-neutral system are similar to the one observed in the previous chapters: energy efficiency, deployment of local REs, and import of both electricity and renewable fuels. In addition, the results obtained provide the road-map to reach carbon neutrality, i.e. the investment planning from 2015 up to 2050. The transition in the different sectors is progressive, e.g. electrification increases almost linearly by 1.8 TWh/y between 2015 and 2050. Only the public mobility and centralised heat sectors are experiencing a disruption. Actually, they appear to be more interesting in terms of costs and emissions. A comparison with two similar studies (see Section 7.2.4) showed that the cost, the energy consumption and the distribution of investments from the model were consistent with the literature.

Although the defossilisation will take place progressively, the analysis of other scenarios shows the importance of anticipating investments. Indeed, if the transition is delayed by 5 years, this will have a negative impact in terms of costs and emissions. Or, if there is reticence to change, some technologies that are not compatible in the future will have to be decommissioned prematurely,

¹⁰Considering an extension of the current reactors, it is assumed that the electricity production is not variable.

implying unnecessary expenses. In a nutshell, inaction has a negative impact on the energy system in terms of costs and emissions. The advantage of optimising the overall transition is that investments will be minimised and spread over the entire transition period. Moreover, a global vision gives legitimacy to the choices that could appear to be sub-optimal at the level of a sector. Such as the massive deployment of electrical heat pumps which are more expensive but necessary to facilitate the integration of intermittent renewables.

From the financial point of view, the transition requires an investment of 13.1 b€₂₀₁₅ per year, which is 20% more expensive than making no defossilisation (10.6 b€₂₀₁₅ per year). These additional investments are made mainly in the massive implementation of PV, storage technologies and electrical HPs. These technologies enable a reduction of primary energy supply, and consequently in a reduced operating cost of 0.2 b€/y. Among the 13.1 b€ investment required: 8.7 b€/y are used to renew the vehicle fleets (cars, buses, trains, trucks, etc.); 2.7 b€/y are used to deploy the wind and solar potential while investing in backup capacities (0.1 b€/y for CCGTs) and reinforcing the grid (0.6 b€/y); 1.1 b€/y are used to electrify heat (0.7 b€/y), implement a heating network (0.2 b€/y), renew CHP and boilers (0.2 b€/y); the remaining 0.6 b€/y are used to deploy storage (0.3 b€/y), fuel conversion technologies (0.2 b€/y) and efficiency measures (0.1 b€/y). The annual investment can be compared to the maintenance expenses (3.9 b€/y) and resources purchase (11.2 b€/y). Maintenance expenses decrease throughout the transition, mainly because vehicles switch from internal combustion engines to electric motors and fuel cells. Resources expenditure decreases initially and then rises again as renewable fuels start to be imported and are more expensive than their equivalent fossil fuels.

The last section shows how accounting for uncertainties will support enlightened decision. When uncertainties are taken into account, the investment strategy (i.e. the technologies deployed) may vary in some sectors. The most impacting technology are FCs that may become the new standard in the mobility and decentralised heat sectors; or that may remain unused. This will depend on the efficiency gains and prices that will be achieved for this technology. To facilitate long-term planning, it is necessary to have a clearer view on these parameters, and thus reduce their uncertainty. This implies the implementation of measures, such as support for the development of demonstrators, long-term policies with a market development framework, a guarantee of technology use, research funds, etc.

Conclusions

Overview

- Summary of the main contributions
- Recommendations and guidance to plan the energy transition pathway
- Future perspectives

In the literature, no consensus is reached on the optimal approach to mitigate greenhouse gas (GHG) emissions and defossilise the energy system. Some would advise to switch to full-electrification of all sectors, including aviation; while others would promote to substitute fossil fuels by renewable ones, such as bio-gas instead of natural gas. In the first case, massive deployment of battery storage would ensure the adequacy between production and consumption; while in the second, the storage of molecules would be favored. A methodology that allows the best compromise to emerge must enable the different options to be expressed.

The initial research question raised in this work was: “*What is the role of energy storage technologies for the energy transition?*”. This research question imposes a framework according to two axis. The ‘*role of storage*’ requires a sufficiently fine resolution of the technologies within the energy system; and the ‘*energy transition*’ qualifies the time horizon.

To satisfy the fine resolution, it is necessary to take a step back and understand the general role of energy storage. Storage is the cornerstone of ensuring adequacy between production and demand. Understanding the role of storage requires the inclusion of energy production and demand. A storage facility can be considered as a system with a demand, a production but also a level of charge. It can cycle on a daily, weekly or even yearly basis. As a consequence, analysing storage implies studying the entire energy system and including a sufficiently fine resolution over a fairly long time horizon. This need for energy modelling justifies the first two contributions of this thesis: a literature review of existing models and the improvement of one of them to reach the required resolution for storage technologies.

To satisfy the time horizon, it is necessary to consider the energy system from now until a future

Conclusions

in which emission neutrality is achieved. During the transition, the mix of storage technologies will vary according to the needs of the energy system. Understanding the role of storage requires to understand when and why technologies are installed and how they are used. To address this need, the third major contribution has been the extension of the EnergyScope TD model into a pathway model. In the latter, the investments are made several times (every 5 years) during the transition period (2015 to 2050).

From the model to the results, the last necessary ingredients are the data. As another contribution of this thesis, data have been collected and detailed in an open-data spirit (see Appendix C). However, these data are fraught with uncertainty. To qualify the results, the final contribution of this thesis is the application of the polynomial chaos expansion (PCE) method to the EnergyScope TD model in order to realise a global sensitivity analysis (GSA).

The combination of the mentioned achievements of this thesis provides a framework for generating several energy transition paths. The resulting models, EnergyScope TD and EnergyScope Pathway, address energy system sizing issues with a perfect foresight approach. The multi-sectoral approaches combined with an hourly resolution over a year offers an accurate representation of storage technologies and enables its analysis. Finally, the development of the models was performed with the objective of maintaining them as open-source tools to foster collaboration among researchers and beyond. Nevertheless, these models are not tailored for all purposes and they do not cover the following topics: spatial resolution, networks adequacy and market equilibrium. Perspectives for these limitations are proposed later.

Methodological contributions

Scenario analysis and system planning are complementary approaches to define a road-map for the energy transition. No strategy should be ruled out *a priori*. By applying the first approach to a snapshot year, a multitude of scenarios can be investigated and compared. It consolidates the ‘*why*’ for the optimum scenario. Then, by applying the second approach, a transition pathway is defined and it enables the ‘*how*’ to modify today’s energy system to reach the optimum in 2050. The methodological contributions of this thesis are detailed hereafter.

(M-1) Review and classification of open-models. A galaxy of models exists for energy systems (483 in a recent review [31]), each oriented towards answering a specific question. In Chapter 1, 54 open-source models were reviewed on the basis of four criteria: (i) be a ‘*whole*’ energy system and allow sector coupling; (ii) be an open-source and open-data documented model; (iii) optimise both the design and hourly operation over a year; (iv) have a short computational cost (around a minute) to be suitable for uncertainty quantification. None of the models directly answers these four criteria. Thus, one model has been identified as a good candidate

to be improved: EnergyScope monthly [35]. This model verifies all the criteria except it has a monthly resolution of the operation.

- (M-2) **EnergyScope Typical Days.** To improve the identified monthly-based model into an hourly one, the main challenge was to keep an acceptable calculation time. For this purpose, inspired by the work of Gabrielli et al. [76], the hourly resolution is based on typical days and a reconstruction method allows the representation of a year and its phenomena at several scales (days, weeks, seasons). It results in a new version of the model presented in Chapter 2 and called EnergyScope TD. This is an open-source - fully documented - energy model which optimises the design and hourly resolution of a whole-energy system within a minute and for a target future year. The model can be downloaded and used out of the box [69].
- (M-3) **EnergyScope Pathway.** The previous model is tailored for scenario analysis and it has been extended into an energy pathway model. The challenges were: how to implement ageing technologies, how to link one year to the next one, how to represent the society inertia, and how to account for the total costs and emissions of the transition. Chapter 3 illustrates the methods developed to keep a concise linear formulation and an acceptable calculation time (10 hours). The model can be downloaded on its repository [71].
- (M-4) **Database for the Belgian energy transition case study.** The case of Belgium was selected to apply the models. The data necessary to represent the complete energy system from 2015 to 2050 were collected on the basis of multiple works. In Chapter 4 and Appendix C, these data are presented with their sources. Furthermore, the consistency of key numerical values have been verified. It results in a complete database for the Belgian energy system.
- (M-5) **Methodology to apply the polynomial chaos expansion (PCE) to a whole-energy system.** This method, presented in chapter 6 and Appendix D, enables the application of a global sensitivity analysis (GSA) to all the uncertain parameters of the system. Through this study, the most critical parameters are identified and their uncertainty quantified. Accounting for their uncertainties allows to qualify the deterministic result. Results show that it is difficult to identify these parameters '*a priori*' in a whole-energy system and motivates the use of a GSA.

Application outcomes

To go from the model to the results, a case study and its data are needed. Some results are direct consequences of the data set used (*data results*), while other results are the consequence of using the data through the model (*model results*). The latter reflects the methodological contribution of this thesis.

The following two results are direct consequences of the assumptions.

- (A-1) **Belgium could quadruple its endogenous renewable energy production.** Indeed, the estimated potential of the Kingdom is: solar (61.6 TWh/y), digestible biomass (38.9 TWh/y),

Conclusions

lignocellulosic biomass (23.4 TWh/y), onshore wind (21.3 TWh/y), offshore wind (14.4 TWh/y) and other more marginals, such as hydro (0.5 TWh/y). In total, 160 TWh of renewable energy could be harvested every year in Belgium, compared to less than 40 TWh - mainly biomass - that have been actually used in 2015.

- (A-2) Investment for the transition are lower than the renewal of the vehicles.** During the transition, there is a strong disproportion between the investments required in the different sectors. Mobility (302 b€) accounts for almost two thirds of the investment required during the transition (466 b€) (in line with other studies [101, 148]). By way of comparison, deploying and renewing the intermittent renewable potential costs 42 b€ for PV and 30 b€ for wind turbines; doing the same for heat production (i.e. CHP, boilers and HP) costs 32 b€; or even reinforcing the electricity grid is estimated at 22 b€.

The following results are outcomes of the model applied to the Belgian case:

- (A-3) Efficiency, renewables and imports are complementary.** These three options, in synergy, enable the carbon-neutrality objective to be achieved. The use of more efficient technologies contributes to this objective as it allows to reduce the primary energy consumed by 40% compared to 2015. Local renewable energies can then contribute up to half of the energy consumed. Importing electricity is a manner of compensating for the intermittent renewable production shortfalls. However, even if electricity imports double or triple compared to the last decades, they will hardly represent more than 10% of the required primary energy (35 TWh/y).
- (A-4) Electrification is key but not the sole.** To allow the coupling of the electricity sector to the heat and mobility ones enables two advantages. First, it facilitates the deployment of efficient technologies: replacing fossil fuels with electricity in these sectors reduces the demand for primary energy through the use of heat pumps or electric vehicles (trains, buses, etc.). Second, it facilitates the integration of intermittent RE: PV and wind turbines produce electricity that is preferable to consume as such. Indeed, electrification enables the implementation of flexible consumers, such as heat pumps coupled with thermal storage or electric vehicle (EV) that can perform smart charging. However, EV deployment is limited in two aspects. From a demand perspective, it is not economically interesting to electrify all the demand, such as private mobility or high temperature heat, as it stresses the electric system in winter. From the production perspective, all the RE potential is used, thus increasing the production implies to import renewable fuels that could be directly used in the other sectors (i.e. hydrogen for mobility). This result is contrary to the current trend that favours electric vehicles. While looking at a whole energy system, the production of electricity is limited to 175 TWh/y (i.e. twice more than in 2015) and cannot supply all types of demand. Enabling the competition between sectors shows that electrifying the low temperature heat is more beneficial than electrifying the private vehicles.

- (A-5) **No defossilisation option should be ruled out.** There is still uncertainty about available resources or options, in particular geothermal potential and the use of nuclear energy. The beneficial impact of increasing these resources have been investigated for wind, solar, imported electricity, geothermal and nuclear. As a result, the total system cost is cheaper when relying on these resources compared to the import of renewable fuels to phase out fossil fuels in the energy system. Moreover, these options are complementary and there is not a single one dominating. The optimum lies in a mix of them.
- (A-6) **Only a few parameters influence the uncertainty of the objective.** Indeed, the global sensitivity analysis shows that around fifteen parameters have an influence on the total cost of the system during the transition. In particular, four families of parameters need to be carefully monitored: fuel cells cost and efficiency, the price of renewable fuels, the price of fossil fuels and the authorised nuclear capacity. Reducing the uncertainty on these four parameters would reduce the uncertainty on the total cost of the energy system by up to 80%.
- (A-7) **Analysing the pathway provides a road-map for the investments.** As a complement to the EnergyScope TD model which focuses on one year independently of the existing energy system, EnergyScope pathway enables the optimisation of the energy strategy and investments from today to the long-term objective. This version identifies the prioritisation to be made between the different sectors and answers ‘*when*’ investments are optimum. As an illustration, investing in batteries happens after electrifying the heat sector.

Recommendations and guidance

Based on the obtained results for Belgium and their analysis, some recommendations and guidance are provided to policy makers. Most of these recommendations could be extended to other European countries.

- (R-1) **System thinking vs. sector thinking.** The system optimum is far from the sum of sector optimums. As an example, to reduce the integration cost of intermittent renewables in the electricity sector, electric heat pumps are installed in the heat sector. Cheaper solutions exist for the latter sector, but the financial benefit on all sectors remains greater. Achieving the optimal solution requires a global vision of the system with compensation mechanisms from one sector to another. This finding is in line with a recent communication of the European institutions [151].
- (R-2) **Belgium’s renewable potential is the cheapest resource.** Deploying the full potential of renewable, with the exception of PV, is the most cost-effective option to reduce the GHG emissions (data result). For PV, a capacity around 20 GW can be deployed with competitive integration costs (model result). At higher capacity, electrolyzers and batteries are required, which implies a greater system cost imputed to PV. If additional renewable resources were proven (geothermal, offshore wind, etc.), it would be beneficial for the system. The same con-

clusion can be drawn about nuclear energy. Furthermore, no competition has been observed between nuclear and renewables energies.

- (R-3) Energy efficiency is key.** For the same energy service, the quantity of primary resources used can be drastically reduced (see A-2). Some efficient technologies are also cheaper, such as public mobility instead of private mobility. The other efficient technologies will become interesting as they offer a reduction in GHG emissions related to the decrease of primary energy needed. Nevertheless, the promotion of these technologies must be done in parallel with measures limiting the *rebound* effect. Indeed, learning from the past, the implementation of efficient technologies often leads to an increase in energy services demand, sometimes resulting in an increase in primary energy consumption [152]. This phenomenon is called the rebound effect or Jevons paradox. Sorrell et al. [152] proposed an illustration of this paradox: *‘since fuel efficient vehicles make travel cheaper, consumers may choose to drive further and/or more often, thereby offsetting some of the energy savings achieved’*.
- (R-4) Critical parameters need to be more deeply analysed.** To reduce future uncertainty and facilitate the choice of policy makers, a few parameters need to be studied, mainly: the use of fuel cells in mobility, the price of future fossil and renewable fuels and whether or not to extend nuclear power. Decision today could mitigate their impact tomorrow and facilitate policy makers to drive our society to carbon neutrality. Hereafter are two examples of measure that could reduce the impact of uncertainties on tomorrow energy system. Subsiding research in the fuel cell field can decrease the uncertainty on their cost or efficiency. Supporting the synthesis of renewable fuel demonstrators (electro or bio) is another way to reduce the uncertainty on their future costs.
- (R-5) The system needs to prepare gradually for the transition.** The implementation of certain technologies makes it possible to gradually prepare the system to switch from fossil resources. For example, the progressive deployment of fuel cell vehicles drives the demand for hydrogen. The latter is first supplied by steam reforming of natural gas and then defossilised by using renewable hydrogen from electrolysis or imports. To mitigate the industrial risk of developing a new sector (i.e. hydrogen), it is preferable to have a long-term vision and that, progressively, a rising demand pulls on a need of hydrogen, rather than the opposite.
- (R-6) Today’s choices must be coherent with long term objectives.** The technologies deployed today will exist for decades and therefore in an energy system where GHG emissions are lower. In order to avoid the premature dismantling of technologies that are no longer in line with climate targets, technologies installed now must ensure compatibility throughout their entire lifetime. Therefore, the premature banning of certain technologies is beneficial on the long term savings, even if it represents an increased cost today. For example, installing an oil boiler in 2020 implies that it can exist until 2040; by that time, the use of oil will be severely disadvantaged. Therefore, it is better for the long term to install a technology based on gas or electricity in 2020.

Perspectives

The work presented can be improved in many ways. Methodologically, the models can always be developed. The case study can be adapted by implementing new technologies or by updating the characteristics of the technologies. And all this can result in new studies. The main perspectives for the future are described below with ideas to improve the work.

- (P-1) **The development of a model is a continuous effort.** The implementation of promising technologies is a continuous work that needs to be updated regularly. For example, the EnergyScope TD model has been improved three times in the last three years ([153], [97] and this manuscript). However, at the time of writing new technologies appear also as good candidates. As an example, carbon capture and sequestration technologies could enable Belgium to balance out an excessive use of fossil fuels during the transition. If Belgium does not respect its commitments, it could use its sequestration potential of about 1 Gt of CO₂ to offset its excess emissions [154]. As another example, the representation of non-energy demand could be implemented more accurately. In the future, products made from energy molecules will continue to be used. The feedstocks needed are not negligible in terms of energy (e.g. a sixth of primary energy consumed in Belgium in 2015 [2]). Including this sector enables a better representation of the energy system, but also be used to the promotion of certain fuels - for non-energy demand - which could be used in other sectors, such as ammonia or methanol for mobility or electricity production. As a last example related to the previous one, the renewable fuel chain can be improved to discretise the synthetic liquid fuel catch-all term into different molecules as well as their specific production and consumption. Finally, the import of these molecules also raises questions outside the scope of the present model version.
- (P-2) **Sensitivity analysis can be extended to robust optimisation.** The work related to sensitivity analysis can be improved in many ways. In this version, the uncertainty characterisation is mainly based on Swiss data. Furthermore, the global sensitivity analysis (GSA) is a preliminary step to the application of robust optimisation methods. This latter determines the energy strategy that minimises the risk (i.e. output variance). Finally, the GSA could be applied to other key performance indicators, such as the GHG emissions or the investment strategy.
- (P-3) **Coupling with other models.** One model cannot answer all questions. For this purpose, a model can be extended indefinitely in different directions and reach levels of complexity beyond the capability of a sole developer. Another solution is to couple the model to others, where the role of each model is carefully defined. This second approach is preferred to complement gaps in the current model. The role of EnergyScope is limited to the system design. Another model could be used to check the adequacy of the networks. By iterating between the two, a realistic design and operation strategy is obtained. As an illustration, in their master thesis, Coates and Percy [93] have coupled the EnergyScope TD and the Dispa-SET models. The second one has an accurate technical resolution of the dispatch and do verify the adequacy of the power grid. Preliminary results show that the dimensioning of the

storage in EnergyScope TD is slightly underestimated and that strategic reserves - necessary for the grid security - are not accounted for. The coupling of models can be extended beyond the technical sphere. For instance, coupling the model to a market one would enable the calculation of energy prices volatility (i.e. electricity market); or coupling the model to an economic one would estimate the impact of the energy transition on other sectors and answer questions such as the raw materials needed, the labour availability, etc. Developing a set of models, that can easily be coupled, would provide a suitable solution in order to, on the one hand, keep understandable models, and on the other hand, obtain extensive results.

(P-4) Extend the EnergyScope TD model. Similarly to the pathway extension, other extensions could be built based on the EnergyScope TD model. For instance, in their master thesis, Thiran and Hernandez [155] extended the model to a multi-cell one enabling the representation of a multi-country case; Boonen and Moraine [156] adapted the problem formulation to be representative of a smaller scale energy system, such as a house or a district. Additionally, the model could be applied to other case studies. Dommissse and Tychon [157] applied the model to the 27th european union countries, one by one, in order to classify the countries by lack or excess of renewable resources compared to their energy demand.

The achieved work is based on a technico-economical optimum where the demand is in line with today's societal need. Perhaps metamorphosing the energy sector is not the single solution neither the simplest one. If it seems too complicated to implement, then perhaps we should question our energy needs in developed countries. Addressing the issue of energy transition is not just a technical problem. We must learn from the past failures where social acceptability wasn't accounted for in the studies.

Hagens [158] demonstrates why humans are minimising the problem of global warming based on six intrinsic behavioural characteristics that are written in our genes. In a nutshell, humans are motivated by the positive stimuli delivered by our brain each time we desire to have better compared to others. Is this a problem? If we interpret it as a willingness to consume more, it could be; but if we interpret it as a desire to enhance our well-being, then there is still room for improvement! In fact, over the last 40 years, the level of happiness has been decreasing in some developed countries where wealth is increasing (e.g. the USA) [159]. The link between happiness and energy consumed is uncorrelated in developed countries [160, 161]. Kantenbacher [162] illustrates this fact with many examples and suggests: *'an effective avenue for prompting less consumptive and more enjoyable behaviors may lie in enhancing the salience of time and downplaying the role of money in time-use decisions'*. Promoting a reduction of the energy demand would facilitate the defossilisation of the system. The only nuance in the concept of demand reduction is the perception: if it is undergone, it is called poverty; but if it is wilful, it is called sobriety.

The difficulty we have in solving the climate change crisis lies in human incoherence, which Edward Osborne Wilson summarises as: *'the real problem of humanity is the following: we have Paleolithic emotions, medieval institutions, and god-like technology'*.

A Review of existing energy models

Overview

- Extensive review of models for scenario analysis

This appendix is an extension of the review presented in Chapter 1 as it accounts for 54 open source or access models. The review has already have been presented in [25].

This appendix provides a review of the different models present in the literature and identifies those that fulfil the following four criteria: be a ‘*whole*’ energy system and allow sector coupling; be an open source and open data documented model; optimise both the design and hourly operation over a year; have a short computational cost (around a minute) to be suitable for uncertainty quantification. This review is built on previous work by Connolly et al. [32], Pfenninger, Hawkes, and Keirstead [47], Zerrahn and Schill [52] and Moret [46]. Also, data from the Open Energy Modelling Initiative [36] platform are integrated in the analysis. This platform “*aims to share open models and open data, in order to advance knowledge and lead to better energy policies. Open up energy models improves quality, transparency, and credibility, leading to better research and policy advice.*” [36].

A.1 Comparison of reviewed models

On the basis of these sources, a list of 54 models is identified and includes the models that are intended to be partially open¹. The previous criteria expressed in the following questions: (i-iii) Does the model include electricity, heat or mobility sector? (iv) Is the model freely available? (v) Is the model open source/access? (vi) Does it optimise the operation strategy? (vii) Does it optimise the investment strategy? (viii) What is the time resolution? (ix) What is the computational time?

¹This work was performed in 2019, since new models have been added on the OpenMod platform and are not accounted in this review. In addition, other models may have been improved and their features may be out-dated.

Appendix A. Review of existing energy models

It is not always explicitly stated whether or not a model meets a criteria. To face this issue, the authors have declined four status; the criteria can be: satisfied, partially satisfied, unsatisfied or no data found. A criteria is satisfied if it is explicitly stated in a review, or if a study/publication based on the model account for the characteristic. As an example, the Calliope model is described in the OpenMod-initiative [36] to include ‘*user dependent*’ sectors. Indeed, it allows the implementation of new layers and thus do not limit the number of sectors. However, out of the 18 publications reported on the official website [48] (consulted the 22/01/2021), none include explicitly the mobility. Thus, the criteria is partially satisfied. For some models, data weren't found to define if a criteria is or not satisfied even partially. Finally, for the *time resolution* and *computational times* criteria, the numerical data found depends on the data. As an example, a model with user defined time resolution can take between seconds to hours to solve the problem. In that situation, the most favourable data are reported.

Table A.1 – Comparison models based on [32] and openmod-initiative [36]. Criteria are satisfied (✓), partially satisfied (✓), unsatisfied (blank) or no data were found (-). Abbreviations: electricity (elec.), hours (h), investment (inv.), mobility (mob.), months (mo), minutes (m), operation (oper.), time resolution (res.), seconds (s) and years (y).

Model	Sectors			Open		Opti.		Time	
	elec.	heat	mob.	access	source	oper.	inv.	res.	run
Balmorel [32, 36, 163]	✓	✓		✓	✓	✓	✓	h	m
BCHPS.T. [32, 164]				✓		✓		h	-
Calliope [36, 47, 48]	✓	✓ ²	✓ ⁹	✓	✓	✓	✓	h	m
COMPOSE [32, 49]	✓	✓	✓	✓		✓	✓	h	-
DESSTinEE [36, 50, 51]	✓	✓	✓	✓	✓			h	h
DIETER [36, 52]	✓	✓	✓	✓	✓	✓	✓	h	m
Dispa-SET [36, 39]	✓			✓	✓	✓		h	h
DynPP [36, 165]	✓	✓ ²					✓	s	h
ELMOD [36, 166]	✓	✓ ²		✓	✓	✓		h	m
EMINENT [32]	✓	✓		✓				y	-
EMLab-Generation [36, 167]	✓			✓	✓			y	h
EMMA [36, 37]	✓			✓	✓	✓	✓	h	m
EnergyNumbers-Bal. [36, 168]	✓			✓ ³	✓			h	s
EnergyPLAN [32, 44]	✓	✓	✓	✓		✓ ⁴		h	s
EnergyScope monthly [46, 53]	✓	✓	✓	✓	✓	✓	✓	m	s
EnergyRt [36, 169]	✓	-	-	✓	✓	-	-	-	m

² CHPs technologies implemented

³ Not directly downloadble.

⁴Based on an user defined decisions order.

A.1. Comparison of reviewed models

Model	Sectors			Open		Opti.		Time	
	elec.	heat	mob.	access	source	oper.	inv.	res.	run
EnergyTrans.Mod. [36, 170]	✓	✓ ²		✓	✓			y	s
ENPEP-BALANCE [32]	✓	✓	✓	✓				y	-
ESO-X [36, 171]	✓			✓	✓	✓	✓	h	m
Ficus [36, 172, 173]	✓	✓ ²		✓	✓	✓	✓	m	h
GAMAMOD ⁵ [36, 174]				✓ ⁶		✓	✓	-	m
Genesys [36, 175]	✓			✓ ³	✓		✓	h	m
GridCal [36, 176]	✓			✓	✓	-	-	-	m
HOMER [32, 177]	✓	✓		✓		✓	✓	m	-
IKARUS [32]	✓	✓	✓	✓ ⁷			✓	y	-
Invert [32, 178]	✓	✓	✓	✓			✓	y	-
LEAP [32, 179]	✓	✓	✓	✓ ⁷				y	-
MEDEAS [36, 180]	✓	✓ ²		✓ ³	✓		-	y	h
MiniCAM [32, 181]	✓	✓	✓	✓ ⁷				y	-
MOCES [36, 182]	✓			6				s	m
MultiMod [36, 183, 184]	✓			6		-	-	y	h
NEMO [36, 185]	✓			✓	✓	✓		h	m
NEMS [32, 42, 46, 186]	✓	✓	✓	✓ ⁷				y	h
Oemof [36, 54, 55]	✓	✓	✓	✓	✓	✓	✓	h	m
OnSSET [36, 187, 188]	✓			✓	✓		✓	y	m
ORCED [32]	✓		✓	✓		✓	✓	h	-
OSeMOSYS [36, 56, 57]	✓	✓	✓	✓	✓	✓ ⁸	✓	d	m
PLEXOSOpenEU [36, 43]	✓			✓		✓		h	h
PowerMatcher [36, 189]	✓			✓	✓	-	-	-	m
PyPSA [36, 58, 59]	✓	✓ ⁹	✓ ⁹	✓	✓	✓	✓	h	m
Renpass [36, 190, 191]	✓			✓	✓	✓		h	h
RETScreen [32, 192]	✓	✓		✓			✓	mo	-
SciGRID [36, 38, 193]	✓			✓	✓			-	m
SimSES [36, 194, 195]	✓			✓	✓			m	h
SIREN [36, 196]	✓			✓	✓			h	m
SIVAEL [32]	✓	✓		✓				h	-
StELMOD [36, 197, 198]	✓			✓	✓	✓		h	m
STREAM [32, 40]	✓	✓	✓	✓ ⁷				h	-

⁵Natural Gas Market oriented

⁶Planned to open up in the future.

⁷Free under conditions.

⁸Operation is usually not resolved on a hourly base.

⁹The model focuses on Power system.

Appendix A. Review of existing energy models

Model	Sectors			Open		Opti.		Time	
	elec.	heat	mob.	access	source	oper.	inv.	res.	run
Switch [36, 60, 61]	✓	✓ ⁹	✓ ⁹	✓	✓	✓	✓	h	h
Temoa [36, 199, 200]	✓	✓	✓	✓	✓		✓	y	m
TIMSEvora [36]	✓	✓ ²		6		✓ ¹⁰	✓ ¹⁰	mo	m
TIMES-PT [36]	✓	✓ ²		6		✓ ¹⁰	✓ ¹⁰	mo	m
TransiEnt [36, 201, 202]	✓	✓ ²		✓	✓			s	h
URBS [36, 62, 63]	✓	✓ ⁹	✓ ⁹	✓	✓	✓	✓	h	h

A.2 Energy model suitable for scenario analysis

Each energy model has its specificities and framework, which makes it suitable to answer different questions. As presented in Chapter 1, the different modelling frameworks proposed in the literature have their advantages but feature one or more of the following limitations defined in this thesis: (i) being limited to only one sector (usually the electricity sector) and representing sectors with different level of details (usually by simplifying heating and mobility sectors); (ii) being commercial, i.e. not freely available nor open source; (iii) not optimising both the investment and the hourly operation strategy; (iv) being too computationally slow to perform multiple evaluation on a short time to do a sensitivity analysis.

Whole energy system

From an historical perspective, energy system models have been focusing on separate sectors, avoiding interactions among them. For example, the gas sector was focusing on the supply of gas from resources to end users without considering technologies such as power to gas. Most of the energy models were and are still focusing on the power sector. This is a consequence of the difficulty to manage and balance the power grid.

Out of the 54 presented models, 19 are focusing on the power system without considering other sectors. A good example of these models is the European Electricity Market Model (EMMA) [37], which is a dispatch optimisation model which focuses on the balancing and flexibility problems in the European grid. Thus, similarly to the following examples, this model is not tailored for our applications. Obviously, it is designed for needs out of the scope of this thesis.

More recently, multi-sectors models have been developed. These models usually focus on one sector and allow a partial implementation of the others. The two main issues that these models are facing

¹⁰ Not directly specified. However TIMES model usually optimises both operations and investments.

are: (i) partial representation of sectors; (ii) incomplete representation of the energy system. As an example of (i), DIETER [52] represents the electricity sector and allows sector coupling through power to heat and electric vehicle [36]. However, the representation of these sectors is done only partially. As an example of (ii), ELMOD [166] focuses on the electricity and heat sectors without accounting for mobility.

Out of the 54 models, 11 of them offer a framework where the electricity, heat and mobility sectors can be implemented. The most famous example being EnergyPLAN[44], a simulation software that represents a complex whole-energy system at a national scale.

Freely available and open source

Some energy models are oriented to commercial applications, such as operation and control or to support investor decisions. For example, a building which has both a boiler and a CHP requires an energy management system to optimise the use of the boiler and/or of the CHP. Energy models, such as PLEXOS[43], aim at supporting investors. These models usually model the market-equilibrium, which is necessary to compute the market price. This information is unavoidable to assess if an investment in the market is going to be profitable or not. Since these energy model can directly be used for commercial applications, they are often not open source neither open access, at least for academia.

Out of the 54 reviewed models, 40 are open access and 29 are both open access and open source. The remaining models claim to become open access in a near future.

Not optimising both the investment and the operation strategy

As defined in the Chapter 1, models can either optimise or simulate. In a simulation the degrees of freedom are fixed *a priori* by the modeller, who defines a set of conditions which directly influence the results. Optimisation, instead, can reveal optimal configurations over a large number of available options and degrees of freedom, making it more suitable for analysing complex systems, where many combined alternatives need to be explored. As a drawback, optimization is computationally more expensive, which represents a fundamental barrier for uncertainty applications.

Depending on the application, a model can: (i) simulate both the investment and operation. As an example, EnergyPLAN [44] uses a merit order tree to define its operation strategy while its investments are imposed. The advantage of such model is its very short computational time (seconds) even if the system is complex. (ii) The model can optimise the investment and simulate the operation. Genesys [175] is an example. It optimises the investments with an evolutionary strategy while simulating the operation with a hierarchical management strategy [36]. The advantage of such model is to optimise the investment over multiple years while verifying its operability with a low

Appendix A. Review of existing energy models

computational time (minutes). (iii) The model can optimise the operation with fixed investments. A typical application of these models, such as Dispa-SET [39], is the power grid. The network exists and dispatchers want to optimise the flows in order to minimise the losses. (iv) The model can optimise both the investment and operation. As an example, the commercial software PLEXOS [43] is used by companies to define the best investment strategies while planning the optimal operation taking into account the risk of failure and the maintenance periods of technologies. The major drawback is the high computational time, hence these models usually cover only one sector.

Out of the 54 reviewed models, 16 claim to optimise both the investment and operation.

Not suitable for uncertainty quantification

An energy system can quickly become more complex when it starts to optimise the interactions between a multitude of actors, such as technologies, resources, etc. Depending on the size of the problem, the same model can take computational times of different orders of magnitude. In the case of the EnergyScope Typical Days (EnergyScope TD) model, the model takes 10 seconds when representing the electricity sector alone, where it takes about 1 minute with all the sectors. Other models specify the estimated calculation time depending on the size and complexity required.

The computation time is a critical indicator of whether the model is suitable for uncertainty analysis. Indeed, in optimisation, uncertainty analysis is generally based on the evaluation of multiple scenarios where the data are slightly changed. For instance, the two methods mentioned in the thesis take between a few hundreds and several hundred thousands evaluations. As a result, the calculation time must be of the order of magnitude of a minute in order to make it possible to carry out these evaluations over a period of a few days.

Out of the 54 reviewed models, 25 claim to have a computational around minutes. This number is reduced to 11 when accounting only for optimisation models, and latter reduced to 5 if accounting for - at least partially - sector coupling.

A.3 Selected models

From Table A.1, models which have the following features are reporter in the Introduction (Table 1.1): freely available; with a monthly to hourly time resolution; and modelling, at least partially, mobility and heat supply besides the electricity sector. They are in alphabetical order: Calliope, COMPOSE, DESSTinEE, DIETER, EnergyPLAN, EnergyScope monthly, Oemof, OSeMOSYS, PyPSA, STREAM, Switch and URBS. These models are detailed and discussed in Chapter 1.

B Clustering methods and number of Typical days

Overview

- Comparison of the clustering methods
- Influence of the typical days on the system design and key performance indicators.

This appendix gives the details related to the choice of the clustering methods and the number of typical days, introduced in Chapter 2. It is built on the work previously presented in [25].

In this appendix, we first compare the clustering methods presented in Section 2.1, to identify the one offering the best performance for the case study. The comparison is performed using 12 TDs as a reference. As resorting to TDs can introduce errors, which can vary depending on the chosen number of TDs, then we show how the optimal number of TDs can be identified by finding an appropriate trade-off between accuracy and computational time.

B.1 Clustering method selection

To select the optimal method for our application, we implemented all four methods, presented in Section 2.1, and assessed their performance based on: (i) computational cost, (ii) the clustering error, defined as the sum of the Euclidean distances within a cluster; (iii) the duration curve error, defined as the Euclidean distance between duration curves. The study was performed when developing the first version of EnergyScope TD which focuses on the Swiss energy system. Consequently, the Swiss data has been taken and are presented in [25]. Compared to the Belgian case, the Swiss case differs as it has one extra time series for hydro flows, and the time series for offshore wind has been removed. Since, the **STEP 1** methodology of the new code version didn't change, except the data used (i.e. time series and weights), the findings for the Swiss case are extended to the Belgian one.

B.1.1 Methods

The method implemented and their sources are presented hereafter. Some methods couldn't have been applied directly and required some post-processing.

k-medoids

We used the MATLAB®-embedded clustering algorithm k-medoids. This implementation is based on the works of Gentle, Kaufman, and Rousseuw [82] and Park and Jun [83]. As the results depend on the initial centroids randomly chosen by the algorithm, we use the '*replicate*' option, which sets the number of times to repeat the clustering, each time with a new set of initial centroids. This number is set to 50 000, which is more or less equivalent to 1 hour of computation on a personal laptop.

Domínguez-Muñoz method

This algorithm is presented in Domínguez-Muñoz et al. [81]. The full code is made available on the repository [69] with a user Manuel explaining how to use it.

Poncelet method

This algorithm is presented in [80]. This methodology does not compute the sequence of days. Hence, a post-processing is required to compute the sequence. This post processing computes for each day (d) of the year the closest typical day (TD) by minimising the euclidean distance, Eq. (B.1):

$$\min_{td \in TD} \sqrt{\sum_{h \in H, i \in TIME_SERIES} \omega(i) \cdot (ts(i, h, td) - ts(i, h, d))^2} \quad (B.1)$$

Similarly to the k-medoids method, Poncelet's method tries every combination of TDs, which is again highly combinatorial. Hence, a variant called '*Poncelet-HYB*' is proposed, which resorts on samples of TDs.

B.1.2 Criteria

In the Swiss case, typical days are selected based on five time series: power demand, heat demand, solar radiation, wind production and hydro dams production (these time series are provided in a previous work [25], see its supplementary material available on the repository: <https://github.com/energyscope/EnergyScope/tree/v2.0>). Three of them are related to weather conditions; thus, we decide to impose a weight (ω) of 1 for each weather time series and 3 for the power and heat demands time series. As a consequence, power demand, heat demand and weather have the same

weighting. The methods are compared for 4 and 12 typical days and based on the three following criteria: (i) computational cost; (ii) clustering error; (iii) duration curve error.

Additional sets and parameters

Criteria are defined based on duration curves and time series. They require additional sets and parameters to define them. The parameter ts gives the hourly profile for a given time series ($i \in TIME_SERIES$), an hour of the day ($h \in H$) and a day ($d \in d$). The duration curve works similarly, except that the hour of the year is given ($t \in T$) rather than the day and the hour of the day.

Computational time

The computational cost is measured on a standard personal machine¹. The k-medoids and Poncelet-HYB method are limited to 50 000 replicates which is equivalent to around 1h of computational time. For the Poncelet method, a timeout is imposed at 1 hour, similarly to what is performed in their study [80]. No upper limit is required for the Domínguez-Muñoz method as it runs in less than 1h.

Clustering error

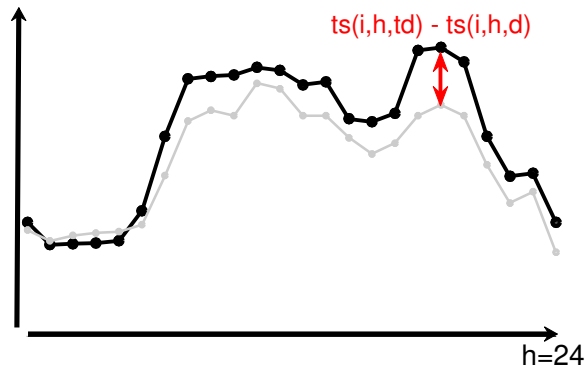


Figure B.1 – Illustration of a the clustering error for the electricity demand time serie ($i=Electricity\ demand$). The black curve represents the typical day 11, which is related to day 347. The Grey curve represents a day $d \in TD_of_day(11)$, in this case $d = 7$. The red arrow represents the distance between these two days at 7 pm ($h = 19$).

¹Intel®Core™ Quad i7-6600U CPU @2.60GHz, with a memory of 8 Go, and a 64-bit system.

Appendix B. Clustering methods and number of Typical days

$$E_{cl} = \sqrt{\sum_{i \in TIME_SERIES, t \in T \setminus \{h, td\} \in T_H_TD(t) | d \in TD_OF_DAY(td) \& d_td \in DAY_OF_TD} \omega(i) \cdot \left(ts(i, h, d_td) - ts(i, h, d) \right)^2} \quad (B.2)$$

$$E_{cl,ref} = \sqrt{\sum_{i \in TIME_SERIES, t \in T \setminus \{h, td\} \in T_H_TD(t) | d_td \in DAY_OF_TD} \omega(i) \cdot \left(ts(i, h, d_td) - \frac{1}{8760} \sum_{d2 \in D, h2 \in H} ts(i, h2, d2) \right)^2} \quad (B.3)$$

Figure B.1 represents the clustering error computation for one day of the year. Eq. (B.2) defines the absolute clustering error (E_{cl}). For each typical day (td), a set of days (d) is associated: the set (TD_OF_DAY) relates days to typical days, e.g. $d \in TD_OF_DAY(td)$ gathers all the days (d) related to the typical day (td). Each typical day is related to a representative day (d_td) and are related by $d_td \in DAY_OF_TD(td)$. These sets can be seen as non-bijective function that link typical days to the days and vice-versa. Based on these sets, Eq. (B.3) defines the reference clustering error ($E_{cl,ref}$). We define the relative error (ε_{cl}) as the ratio between the clustering error (E_{cl}) and the reference clustering error ($E_{cl,ref}$).

Duration curve error

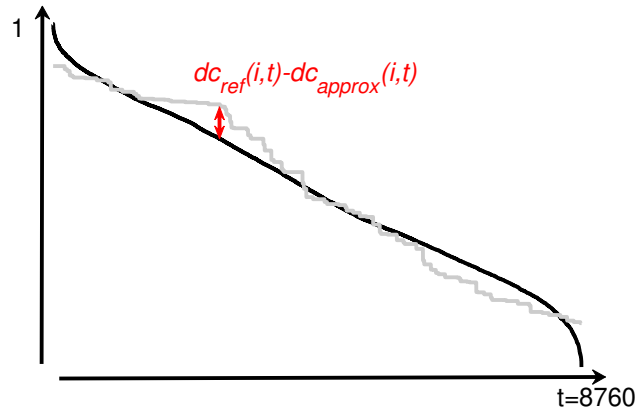


Figure B.2 – Illustration of a duration curve error for the electricity demand (i =“Electricity demand”). The black curve represents the real duration curve based on the 8760 h data. The grey curve represents the approximated duration curve while resorting to 4 TDs and the k-medoids method. The red arrow represents the distance between these two duration curves at a arbitrary hour ($h=2878$).

Figure B.2 represents the duration curve error computation for a time series.

$$E_{dc} = \sqrt{\sum_{i \in TIME_SERIES, t \in T} \omega(i) \cdot \left(dc_{ref}(i, t) - dc_{approx}(i, t) \right)^2} \quad (B.4)$$

$$E_{dc,ref} = \sqrt{\sum_{i \in TIME_SERIES, t \in T} \omega(i) \cdot \left(dc_{ref}(i, t) - \frac{1}{8760} \sum_{t2 \in T} dc_{ref}(i, t2) \right)^2} \quad (B.5)$$

A duration curve illustrates the variation of a certain load in a downward form such that the greatest

load is plotted in the left and the smallest one in the right. In this case, the loads are the hourly capacity factors or the demand. Eq. B.4 defines the absolute duration curve error (E_{dc}). For each time series ($i \in TIME_SERIES$) and every time step ($t \in T$), we compare the real duration curve $dc_{ref}(i, T)$ with the approximated duration curve ($dc_{approx}(i, T)$) based on typical days. Based on Eq. B.5 which defines the reference duration curve error ($E_{dc,ref}$), we define the relative error (ϵ_{cl}) as the ratio between the clustering error (E_{dc}) and the reference clustering error ($E_{dc,ref}$). The reference clustering error is computed as the error made compare to an averaged constant duration curve.

B.1.3 Benchmark

Figure B.3 resorts on 4 TDs and presents three approximated duration curves (power demand, heat demand and sun radiation) compared to the reference one. Figure B.4 resorts on 12 TDs. The four clustering methods offer consistent results. Increasing the number of TDs decreases the space between the approximated duration curves and the real ones.

Tables B.1 and B.2 summarise the performance of the methods while resorting to 4 and 12 typical days respectively.

Table B.1 – Performance of clustering methods to compute 4 typical days.

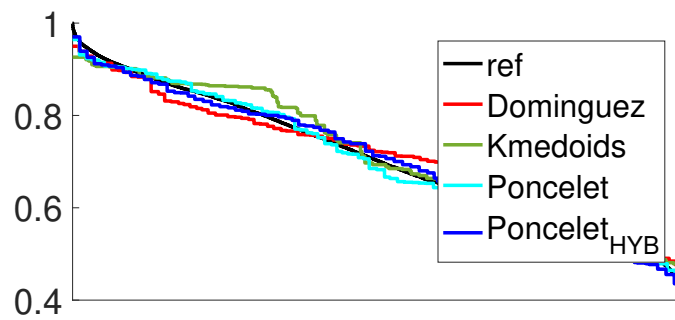
Criteria	Units	k-medoids	Domínguez-Muñoz	Poncelet	Poncelet HYB
Computational cost	[s]	1022	292	3600	3125
Clustering error ϵ_{cl}	[-]	25.9%	10.5%	12.2%	13.3%
Duration curve error ϵ_{dc}	[-]	49.7%	18.3%	20.4%	18.5%

Table B.2 – Performance of clustering methods to compute 12 typical days.

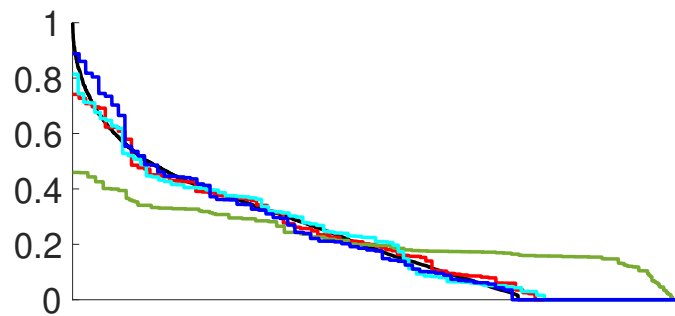
Criteria	Units	k-medoids	Domínguez-Muñoz	Poncelet	Poncelet HYB
Computational cost	[s]	3750	876	3600	3253
Clustering error ϵ_{cl}	[-]	24.4%	9.2%	11.6%	11.6%
Duration curve error ϵ_{dc}	[-]	19.1%	7.7%	12.5%	12.3%

An illustrative example of a cluster for one TD is shown in Figure B.5. In this example, power and heat demand have lower errors compared to the sun power. However, one day has a very different power demand curve, but very similar errors for heat demand and sun power.

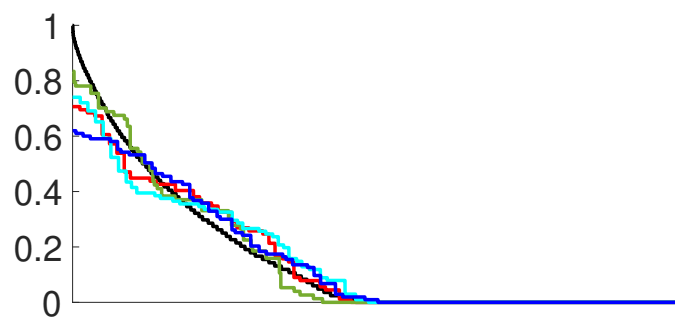
The analysis reveals that the four methods offer consistent results and have an error of the same order of magnitude. However, the method by Domínguez-Muñoz et al. [81] leads to the best results with the lowest computational time. Hence, this method will be used in the following sections.



(a) Power

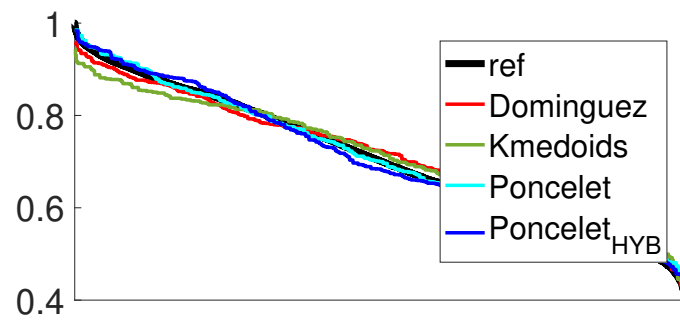


(b) Heat

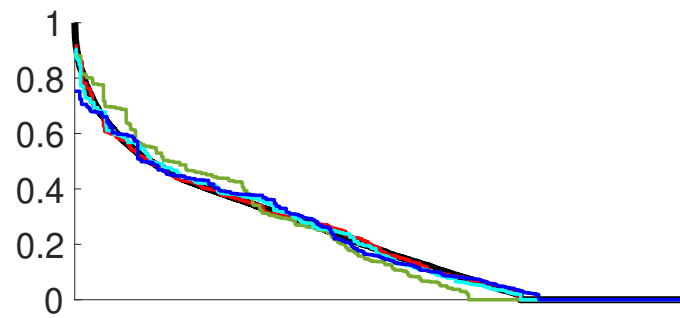


(c) Sun

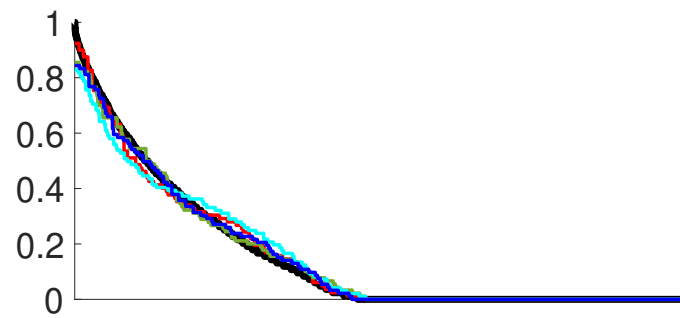
Figure B.3 – Approximation of the duration curves using different clustering methods and 4 typical days. Methods are consistent and similar, except for the k-medoids. Legend: Dominguez stands for the Domínguez-Muñoz method.



(a) Power



(b) Heat



(c) Sun

Figure B.4 – Approximation of the duration curves using different clustering methods and 12 typical days. Methods are consistent and perform better than when resorting to 4 TDs, as presented in Figure B.3.

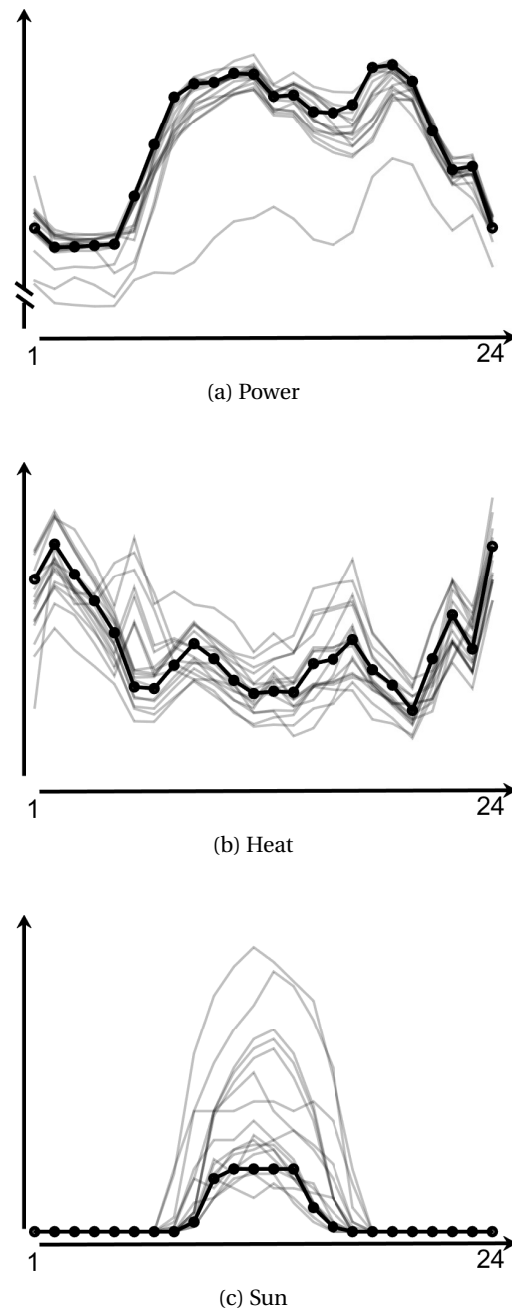


Figure B.5 – Illustration of a cluster: 17 days represented by 1 TD. The thick black dotted line is the selected typical day; the grey lines are the other 16 days represented by the selected TD. X-axis represents the hour of the day.

B.2. Number of typical days influence

Table B.3 – Comparison of results obtained with different numbers of typical days. bCHF/y stands for billion Swiss Francs per year.

		Ref.	48TDs	24TDs	12TDs	8TDs	4TDs	Units
Primary Energy Consumption	Gasoline	7.56	7.56	7.56	7.56	7.56	7.56	TWh/y
	Diesel	13.84	13.84	13.84	13.84	13.84	13.84	TWh/y
	NG	37.10	36.97	36.96	36.95	32.53	37.20	TWh/y
	Elec. Imp.	-	-	-	-	4.12	-	TWh/y
	Elec. Exp.	0.20	0.19	0.14	0.02	0.10	-	TWh/y
	Wind	10.68	10.68	10.68	10.68	10.68	10.68	TWh/y
	Solar	17.37	17.29	17.24	17.11	16.88	17.32	TWh/y
	Geothermal	9.69	9.69	9.69	9.67	9.66	9.66	TWh/y
	Hydro	37.18	37.18	37.18	37.18	37.18	37.18	TWh/y
	Waste	11.14	11.14	11.14	11.14	11.14	11.14	TWh/y
	Oil	5.06	5.13	5.13	5.13	5.09	5.09	TWh/y
Technologies output	Boilers	30.17	29.00	28.16	28.13	34.40	30.99	TWh/y
	HPs	27.33	27.60	27.60	27.60	27.42	26.57	TWh/y
GHG emissions (fuels)		22.51	22.50	22.49	22.47	23.22	22.54	MtCO ₂ -eq/y
System cost		14.34	14.38	14.39	14.33	14.36	14.27	bCHF/y

These results are based on Swiss data, which can to some extent be considered representative of continental European countries; however, results are always case specific. For this reason, Step 1 and Step 2 should be considered as two independent and separate steps. For a new case study, both steps need to be run with the case-specific data. Also, other methods can be used to select TDs in Step 1, while still using the proposed energy model in Step 2.

B.2 Number of typical days influence

We compare the results obtained by applying the EnergyScope TD model with different numbers of TDs to the ‘reference’ solution. The latter, our ground truth for this comparison, is defined as the case in which the model uses 8760h, i.e. without resorting to TDs. This results is obtainable but at a greater computational cost (around 19 hours). The case study is the Swiss energy system presented in [25].

The results are reported in Table B.3. Overall, the approximation offered by TDs appears appropriate. In fact, with regard to key indicators - such as energy consumption, system design, total GHG emissions from fuels and system total annual cost - the chosen number of TDs has little influence on the results.

However, we observe 3 major differences deriving from the TDs approximation, which are reported in Table B.4: (i) the computational time; (ii) the thermal storage capacities; (iii) the strategy to bring

Appendix B. Clustering methods and number of Typical days

flexibility in the electricity sector. The rest of the design is very similar, as presented in Table B.3.

Table B.4 – Comparison of major differences obtained with different numbers of typical days.

		Ref.	48TDs	24TDs	12TDs	8TDs	4TDs	Units
Computational time		70 240	296	135	92	91	54	s
Electricity production	PV	17.37	17.29	17.24	17.11	16.88	17.32	TWh/y
	Wind	10.68	10.68	10.68	10.68	10.68	10.68	TWh/y
	Hydro (all)	37.18	37.18	37.18	37.18	37.18	37.18	TWh/y
	CCGT	1.22	-	-	-	0.39	-	TWh/y
	CHP	3.68	5.00	5.38	5.40	0.20	4.24	TWh/y
	Elec. Imp.	-	-	-	-	4.12	-	TWh/y
Storage capacity	Dec.	41.41	35.85	35.89	35.90	26.65	23.22	GWh
	DHN daily	18.76	16.52	16.53	14.54	11.00	10.27	GWh
	DHN seas.	200.45	145.38	129.72	50.52	-	-	GWh

(i) **Computational time:** as expected, correlation between computational time and number of typical days is verified except for low number of typical days: With less than 12 TDs, the computational time reaches a plateau of around 90s to solve the problem.

(ii) **Thermal storage capacity:** the reference solution relies on daily thermal storage for decentralised and DHN heat. Moreover, it installs a seasonal thermal storage for the DHN in order to shift between days the electricity excess absorbed by the HPs. Figure B.6 presents the energy stored by the DHN seasonal storage over the year for different cycle durations². The reference solution shows that this technology is used for weekly to monthly cycles. By reducing the number of TDs, the energy stored for weekly cycles is reduced and even not captured with less than 12 TDs. However, resorting to 12 TDs captures some intra days event.

(iii) **Strategy to bring flexibility in the electricity sector :** To face the intermittency of RE, the electricity sector can find sources of flexibility in supply, demand or storage. In this scenario, the flexibility comes from hydro dams, thermal storage and electricity production. As the behavior of hydro dams is similar for the different scenarios and thermal storage has been analysed in the previous sections, here we analyse only the difference in the electricity production mix. As shown in Table B.4, when varying the number of TDs, the production mix remains the same for RE technologies, whereas some differences are observed for flexible producers and imports. In the reference solution, the system relies on CHP (75%) and CCGT (25%) to back up the scarcity of intermittent renewable energy during winter. Instead, solutions resorting to TDs have different flexible producers to face lack of electricity during winter, such as CHP or more electricity imports.

²The energy stored per cycle is determined as the total amount of energy which entered and left the storage within a certain period (the storage is considered as a last in first out (LIFO) stack). For example, 1 kWh entering and leaving 10 times/day a storage counts as 10kWh and is accounted in cycle length lower or equal to 24 hours.

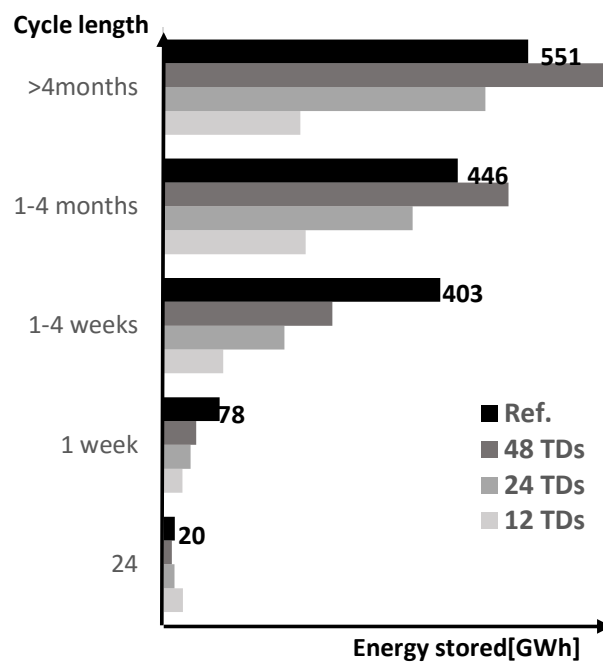


Figure B.6 – Energy stored in the DHN seasonal storage obtained for different cycle length and with different numbers of TDs. With less than 8 TDs, there is no capacity installed.

As an example, the optimal system with 12 TDs exclusively resorts on industrial CHP or the optimal system with 8 TDs mostly relies on electricity imports. These differences between system design strategies can be understood when looking at the objective values. They give similar results which means that solutions are almost equivalent, which is rather typical in LP problems. We thus forced the system design of TDs solution to be the same as the reference solution, and observed differences in objective values of less than 1%.

In summary, resorting to different numbers of TDs results in acceptable differences compared to the reference solution. However, with 8 TDs or less, the intra-days phenomena, such as storing during the weekend and restore during the week, cannot be captured and some technologies are not implemented. Therefore, 12 TDs is a good trade-off between accuracy and computational time. This number of TDs is thus used in the paper.

B.3 Discussion

The selection of typical days (STEP 1) is independent of the use of the LP model which represents the energy system (STEP 2). Previously, we analysed which clustering method selects the ‘best’ typical days, i.e. minimise a clustering and duration curve errors. The revised version of the k-medoids proposed by [81] had the best performance. Therefore, we implemented it in the current code. Nevertheless, it is possible to easily substitute this clustering method by another one.

Appendix B. Clustering methods and number of Typical days

The influence of the number of typical days over the energy system (STEP 2) have been investigated. If the number of typical days is too high, this leads to long calculation times (hours), but on the other hand, if the number of typical days is small, this can lead to designing errors, especially for storage. Using 12 typical days seems to be the best compromise.

Based on 3 years of experience with the use of this model, it has been observed that the selection of typical days has a limited influence on the design results. In our case, what drives the design of the system are the annual demands and capacity factors of the renewables. These are corrected after the selection of the sample days. Indeed, if the average PV capacity factor based on the sequence of typical days is 10.7%, while the historical value is 11.6%, then the implemented value ($c_{p,t}$) will be increased by $11.6/10.7$.

C Belgian energy system data in 2035

Overview

This appendix reports the input data for the application of the LP modeling framework to the case study of Belgium between 2015 and 2050. Data are detailed for the year 2035 and 2015, the latter used for model verification. Trends to extrapolated these data for the other years are given. This appendix is an improved version previously presented in [25, 97]

The data can be grouped into three parts: resources, demand and technologies. For resources, the work of the Joint Research Center (JRC) [108], Biomass atlas [105] and Brynolf et al. [109] have been used to complement and confirm the prices already reported in previous works [25, 46, 133]. For energy demand, the annual demand is calculated from the work of the European Commission's projections up to 2050 [89]. As a complement, the time series are all calculated on the basis of the year 2015. For technologies, they are characterised by the following characteristics: energy balances, cost (investment and maintenance), and environmental impact (global warming potential (GWP)). For weather dependent technologies (wind, solar, etc.), real production for the year 2015 was collected from the TSO.

For GWP and GHG emissions, LCA data are taken from the Ecoinvent database v3.2¹ [113] using the “allocation at the point of substitution” method. GWP is assessed with the “GWP100a - IPCC2013” indicator. For technologies, the GWP impact accounts for the technology construction; for resources, it accounts for extraction, transportation and combustion. In addition, data for fuel combustion are taken from Quaschnig [112].

For the cost, the reported data are the nominal values for Belgium in the year 2035. All costs are expressed in *real*² Euros for the year 2015 (€₂₀₁₅). If not specified, € refers to €₂₀₁₅. All cost data used

¹The database is consulted online: <http://www.ecoinvent.org>

²*Real* values are expressed at the net of inflation. They differ from *nominal* values, which are the actual prices in a

Appendix C. Belgian energy system data in 2035

in the model originally expressed in other currencies or referring to another year are converted to €₂₀₁₅ to offer a coherent comparison. Most of the data come from a previous work [25, 46], and were expressed in CHF₂₀₁₅ (Based on the average annual exchange rate value from European central bank (ECB) <https://www.ecb.europa.eu>, the annual rate was 1€₂₀₁₅ = 1.0679CHF₂₀₁₅). The method used for the year conversion is illustrated by Eq. C.1.

$$c_{inv}[\text{€}_{2015}] = c_{inv}[C_y] \cdot \frac{\text{USD}_y}{C_y} \cdot \frac{\text{CEPCI}_{2015} [\text{USD}_{2015}]}{\text{CEPCI}_y [\text{USD}_y]} \cdot \frac{\text{€}_{2015}}{\text{USD}_{2015}} \quad (\text{C.1})$$

Where C and y are the currency and the year in which the original cost data are expressed, respectively, USD is the symbol of American Dollars and the Chemical Engineering's Plant Cost Index (CEPCI) [203] is an index taking into account the evolution of the equipment cost (values reported in Table C.1). As an example, if the cost data are originally in EUR₂₀₁₀, they are first converted to USD₂₀₁₀, then brought to USD₂₀₁₅ taking into account the evolution of the equipment cost (by using the CEPCI), and finally converted to €₂₀₁₅. The intermediate conversion to USD is motivated by the fact that the CEPCI is expressed in *nominal* USD. Although this conversion method is originally defined for technology-related costs, in this paper as a simplification it used also for the cost of resources.

The current appendix is built in three parts. At first, data are given for the year 2035 for resources (Section C.1), demand (Section C.2) and technologies (Section C.3). Then, the year 2015 is discussed as real data have been collected for this case. And finally, the extension of the data from year 2035 to other years are detailed.

C.1 Resources

The availability of all resources, except for biomass, and non-RE waste, is set to a value high enough to allow unlimited use in the model. Table C.2 details the prices of resources (c_{op}), the GHG emissions (gwp_{op}) associated to their production, transportation and combustion; and endogenous availability of resources. Export of electricity are possible, but they are associated to a zero selling price. Two kinds of emissions are proposed: one accounting for the impact associated to production, transport and combustion (based on GWP100a - IPCC2013 [46]); the other accounting only for combustion (based on Quaschnig [112]). Total emissions are used to assess energy system emissions. Combustion only is used to calculate the direct CO₂ emissions that can be captured and used through a carbon capture technology (latter presented).

given year, accounting for inflation.

Table C.1 – Chemical Engineering's Plant Cost Index (CEPCI) values [203]

Year	CEPCI
1982	285.8
1990	357.6
1991	362.3
1992	367.0
1993	371.7
1994	376.4
1995	381.1
1996	381.7
1997	386.5
1998	389.5
1999	390.6
2000	394.1
2001	394.3
2002	395.6
2003	402.0
2004	444.2
2005	468.2
2006	499.6
2007	525.4
2008	575.4
2009	521.9
2010	550.8
2011	585.7
2012	584.6
2013	567.3
2014	576.1
2015	556.3

C.1.1 Local renewable resources

The majors renewable potentials are: solar, biomass and wind. Additionnaly, Belgium has hydro and perhaps affordable geothermal. Wind, solar, hydro and geothermal are limited by the number of technologies deployable, while biomass is limited by the amount of resources available.

Wind, solar, hydro and geothermal

The estimation of these resources have been done in Chapter 4 (see Section 4.1.1).

Biomass and non-RE waste

In an European study, Elbersen et al. [105] drew the biomass atlas of EU countries for different scenarios in terms of prices and potentials. According to a conservative approach, the sustainable scenario estimations are selected. In their work, biomass is declined in a larger variety of form. To adapt these data to our work, these varieties are aggregated into three types: woody biomass, wet biomass and non-RE waste. Waste accounts for common sludges, MSW landfill, MSW not landfill (composting, recycling) and paper cardboard. The overall potential is estimated to 17.8 TWh/y with an approximate price of 10.0 €/MWh. The price is estimated as a weighted sum between the different variety and their specific price (given in the document). Wet biomass accounts for all the digestible biomass, which are verge gras, perennials (grassy), prunings, total manure, grass cuttings abandoned grassland, animal waste and forrage maize (biogas). The overall potential is estimated to 38.9 TWh/y with an approximate price of 2.5 €/MWh. Woody biomass accounts for all the non-digestible biomass, which are roundwood (including additional harvestable roundwood), black liquor, landscape care wood, other industrial wood residues, perennials (woody), post consumer wood, saw-dust, sawmill by-products (excluding sawdust) and primary forestry residues. The overall potential is estimated to 23.4 TWh/y with an approximate price of 14.3 €/MWh.

Oleaginous (0.395 TWh/y) and sugary (0 TWh/y) potentials are two order of magnitude below the previous categories and thus neglected.

However, these costs do not account for treatment and transportation. Based on a local expert (from Coopeos), a MWh of wood ready to use for small wood boilers is negotiated around 28 €/MWh today, twice much than estimated prices. This order of magnitude is in line with the Joint Research Center price estimation in 2030 [108]. Thus, the price proposed in [105] are doubled. It results in prices for woody biomass, wet biomass and waste of 28.5, 5.0 and 20.0 €/MWh in 2015, respectively. The price for biomass is expected to increase by 27.7% up to 2050 [108]. By adapting these value to 2035, the prices are for 32.8 €/MWh woody biomass, 5.8 €/MWh for wet biomass and for 23.1 €/MWh for waste.

C.1.2 Imported resources

Dominating fossil fuels are implemented in the model and detailed in Section 4.1.2. They can be regrouped in hydrocabons (gasoline, diesel, LFO and NG), coal and uranium. Data is summarised in Table C.2 and are compared to other sources, such as estimations from the Joint Research Center (JRC) of prices for oil, gas and coal [108]. They base their work on a communication of the European Commission [107].

Fuel can also be produced from renewable feedstocks: biomass or renewable electricity. Brynolf et al. [109] estimates a range for the production cost for some electro-fuels based on hydrogen

electrolysis: methane, methanol, DME, gasoline and diesel. Hereafter, we will assume that the price of an electro-fuel is equal to its production cost. In addition, imported bio-fuels are assumed to have the same price as their equivalent electro-fuel. Finally, the costs are estimated in 2015 and 2030 in [109]. As no estimates are made thereafter, the 2030 value is imposed in 2050 and a linear improvement is assumed between 2015 and 2050³.

Table C.2 – Price, GHG emissions and availability of resources, in 2035. Abbreviations: light fuel oil (LFO), natural gas (NG), synthetic liquid fuel (SLF) and synthetic natural gas (SNG).

Resources	c_{op} [€ ₂₀₁₅ /MWh _{fuel}]	gwp_{op} [kgCO ₂ -eq./MWh _{fuel}]	$CO_{2direct}^a$ [kgCO ₂ /MWh _{fuel}]	$avail$ [TWh]
Electricity Import	84.3 ^b	275.3 ^c	0	27.5 ^b
Gasoline	82.4 ^d	345 ^c	250	∞
Diesel	79.7 ^e	315 ^c	270	∞
LFO	60.1 ^f	311.5 ^c	260	∞
NG	44.3 ^g	267 ^c	200	∞
Woody biomass	32.8	11.8 ^c	390	23.4
Wet-biomass	5.8	11.8 ^c	390	38.9
non-RE waste	23.1	150 ^c	260 ^h	17.8
Coal	17.6 ^g	401 [113]	360	∞
Uranium	3.9 ⁱ	3.9 [113]	0	∞
Bio-diesel	240.0 ^j	0 ^k	270	∞
Bio-gasoline	225.7 ^j	0 ^k	250	∞
SLF	211.4 ^j	0 ^k	260	∞
SNG	197.1 ^j	0 ^k	200	∞
H ₂	177.1 ^j	0 ^k	0	∞

^aDirect emissions related to combustion[112].

^b Based on average market price in the year 2010 (50 EUR₂₀₁₀/MWh, from [204]). Projected from 2010 to 2035 using a multiplication factor of 1.36 [205]. For security of supply reason, the availability is limited to 30% of yearly electricity EUD (See Section 4.2.2).

^c GWP100a-IPCC2013 metric: impact associated to production, transport and combustion, see [46]

^dBased on 1.49 CHF₂₀₁₅/L (average price in 2015 for gasoline 95 in Switzerland) [206]. Taxes (0.86 CHF₂₀₁₅/L, [207]) are removed and the difference is projected from 2015 to 2035 using a multiplication factor of 1.24 [208]. In line with [108].

^eBased on 1.55 CHF₂₀₁₅/L (average price in 2015) [206]. Taxes (0.87 CHF₂₀₁₅/L, [207]) are removed and the difference is projected from 2015 to 2035 using a multiplication factor of 1.24 [208]. In line with [108].

^fBased on 0.705 CHF₂₀₁₅/L (average price in 2015 for consumptions above 20000 L/y) [209]. Taxes (0.22 CHF₂₀₁₅/L, [207]) are removed and the difference is projected from 2015 to 2035 using a multiplication factor of 1.24 [208]. In line with [108].

^g Based on the European Commission estimated cost of resources in 2030, see Table 5 from [108].

^h Assuming that the energy content can be assimilated to plastics and extended to LFO.

ⁱ Average of the data points for 2035 in [210], accounting for the efficiency of nuclear power plants (Table C.6).

^j Data extrapolated from [109]

^k Emissions related to electro-fuels and bio-fuels production are neglected.

³This assumption appears to be a clear limitation of the work since the prices of renewable fuels are at the root of the uncertainty about the total cost of energy systems at low GHG emission. As stated in the conclusion, studying the future of renewable fuels is essential to reduce uncertainty about future energy systems.

C.2 Energy demand and political framework

The end-use demand (EUD) for heating, electricity and mobility in 2035 is calculated from the forecast done by the European Commission in 2035 for Belgium (see Appendix 2 in [89]). However, in [89], the final energy consumption (FEC) is given for heating and electricity. The difference between FEC and EUD is detailed in Section 2.2.2 and can be summarised as follows: the FEC is the amount of input energy needed to satisfy the EUD in energy services. Except for HP, the FEC is greater than EUD. We applied a conservative approach by assuming that the EUD equal to the FEC for electricity and heating demand.

C.2.1 Electricity

The values in table C.3 list the electricity demand that is not related to heating for the three sectors in 2035. The overall electricity EUD is given in [89]. However, only the final energy consumption (FEC) is given by sectors. In order to compute the share of electricity by sector, we assume that the electricity to heat ratio for the residential and services remain constant between 2015 and 2035. This ratio can be calculated from European Commission - Eurostat. [128], these ratio of electricity consumed are 24.9% and 58.2% for residential and services, respectively. As a consequence, the industrial electricity demand is equal to the difference between the overall electricity demand and the two other sectors.

A part of the electricity is assumed to be a fixed demand, such as fridges in households and services, or industrial processes. The other part is varying, such as the lighting demand. The ratio between varying electricity and fixed demand are the one of Switzerland, presented in [25, 46] which are based on [205]. The varying demand of electricity is shared over the year according to $\%_{elec}$, which is represented in Figure C.1. We use the real 2015 Belgian electricity demand (data provided by ENTSO-E <https://www.entsoe.eu/>). $\%_{elec}$ time series is the normalised value of the difference between the real time series and its minimum value.

Table C.3 – Yearly electricity demand not related to heating by sector, in 2035.

	Varying [TWh]	Constant [TWh]
Households	0.8	21.9
Industry	4.8	40.0
Services	5.1	20.1

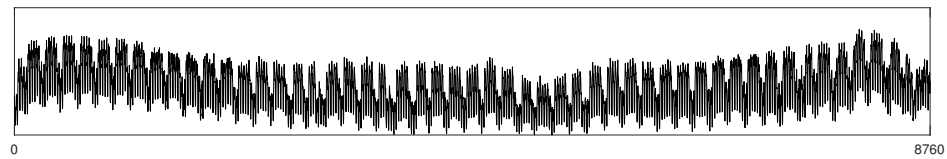


Figure C.1 – Normalised electricity time series over the year.

C.2.2 Heating

We applied the same methodology as in previous paragraph to compute the residential, service heat yearly demand. The industrial heat processes demand is assumed to be the overall industrial energy demand where electricity and non energy use have been removed. Yearly EUD per sector is reported in table C.4.

A part of the heat is assumed to be a fixed demand, such as hot water in households and services, or industrial processes. The other part represents the space heating demand and is varying. Similarly to the electricity, the ratio between varying electricity and fixed demand are the one of Switzerland, presented in [25, 46] which are based on [205]. The varying demand of heat is shared over the year according to $\%_{sh}$. This time series is based on our own calculation. The methodology is the following: based on the temperature time series of Uccle 2015 (data from institut royal météorologique (IRM) [211]); the heat degree hours (HDH) are calculated; and then the time series. The HDH is a similar approach than the more commonly used heat degree days (HDD). According to Wikipedia, HDD is defined as follows: “*HDD is a measurement designed to quantify the demand for energy needed to heat a building. HDD is derived from measurements of outside air temperature. The heating requirements for a given building at a specific location are considered to be directly proportional to the number of HDD at that location. [...] Heating degree days are defined relative to a base temperature*”. According to the European Environment Agency⁴, the base temperature is 15.5°C, we took 16°C. HDH are computed as the difference between ambient temperature and the reference temperature at each hour of the year. If the ambient temperature is above the reference temperature, no heating is needed. Figure C.2 compares the result of our methodology with real value collected by Eurostat⁵. The annual HDD was 2633, where we find 2507.

By normalising the HDH, we find $\%_{sh}$, which is represented in Figure C.3.

C.2.3 Mobility

The annual passenger transport demand in Belgium for 2035 is expected to be 194 billions () [89]. Passenger transport demand is divided between public and private transport. The lower ($\%_{public,min}$)

⁴From <https://www.eea.europa.eu/data-and-maps/indicators/heating-degree-days-2>, consulted the 06-12-2019

⁵Source: <https://ec.europa.eu/eurostat>, consulted the 06/12/2019.

Appendix C. Belgian energy system data in 2035

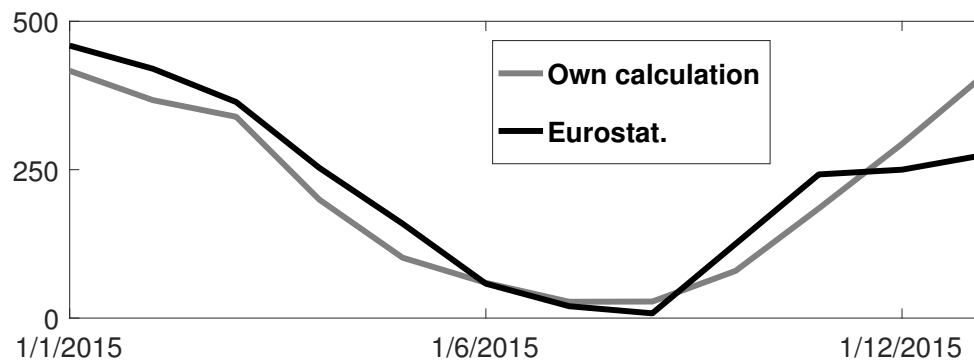


Figure C.2 – Comparison of heat degree days between Eurostat and our own calculation.

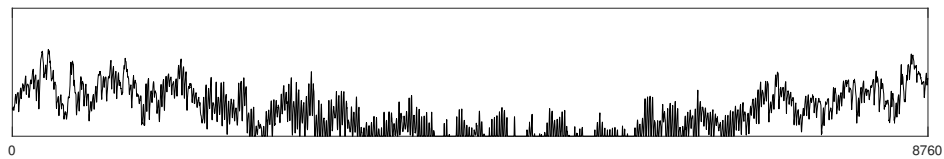


Figure C.3 – Normalised space heating time series over the year.

Table C.4 – Yearly heat end use demand per sector, in 2035.

	Space heating [TWh]	Hot water [TWh]	Process heat ^a [TWh]
Households	65.9	16.8	0
Industry	17.0	5.2	65.3
Services	23.1	4.4	0

^aWe define process heat as the high temperature heat required in the industrial processes. This heat cannot be supplied by technologies such as heat pumps or thermal solar.

and upper bounds ($\%_{public,max}$) for the use of public transport are 19.9%⁶ and 50% of the annual passenger transport demand, respectively. The passenger mobility demand is shared over the day according to $\%_{pass}$. We assume a constant passenger mobility demand for every day of the year. This latter is represented in Figure C.4 (data from Figure 12 of [212]).

The annual freight transport demand in Belgium for 2035 is expected to be 98e09 tons kilometers [89]. The freight can be supplied by trucks, trains or boats. The lower ($\%_{fr,rail,min}$) and upper bounds ($\%_{fr,rail,max}$) for the use of freight trains are 10.9%⁶ and 25% of the annual freight transport demand, respectively. The lower ($\%_{fr,boat,min}$) and upper bounds ($\%_{fr,boat,max}$) for the use of freight inland boats are 15.6%⁶ and 30% of the annual freight transport demand, respectively. The lower ($\%_{fr,trucks,min}$) and upper bounds ($\%_{fr,trucks,max}$) for the use of freight trucks are 0% and 100% of the annual freight transport demand, respectively. The bounds and technologies information are latter summarised in Table C.15.

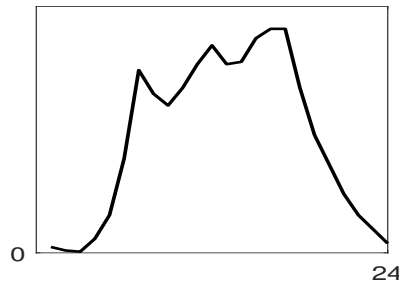


Figure C.4 – Normalised passenger mobility time series over a day. We assume a similar passenger mobility demand over the days of the year.

C.2.4 Discount rate and interest rate

To compute their profitability, companies apply a discount rate to the investment they make. A discount rate is used for both cost of finance and for risk perception and opportunity cost. The cost of finance is to be compared with concepts like ‘hurdle rate’ or ‘rate of return’ usually calculated in accordance to an annual return on investment. Each individual investment physically occurring in year k , results in a stream of payments towards the amortization of this investment spread over several years in the future. The higher the cost of finance (or hurdle rate), the higher the annual payments spread over the lifetime of an investment and thus the higher the total cost. The hurdle rate affects only the investment costs so the impact is bigger for capital intensive technologies. We consider differentiated hurdle discount rates for different groups of energy supply and demand technologies, representing the different risk perception of industry versus individuals.

According with Meinke-Hubeny, De Oliveira, and Duerinck [122] who based their work on the JRC EU TIMES model [108] in line with the PRIMES model [89], the discount rate is around 7.5 up to 12%

⁶ it corresponds to the share of 2015 (From Tables 2.2.3 and 2.3.3 of [92]), in line with data from the SPF [127].

depending on the technologies. Discount rate cannot be directly converted into interest rate as the first is fixed by the market and the second is fixed by the central banks. As the evidence presented in Figure C.5 indicates, while these two interest rates tend to move together, they also may follow different paths from time to time.

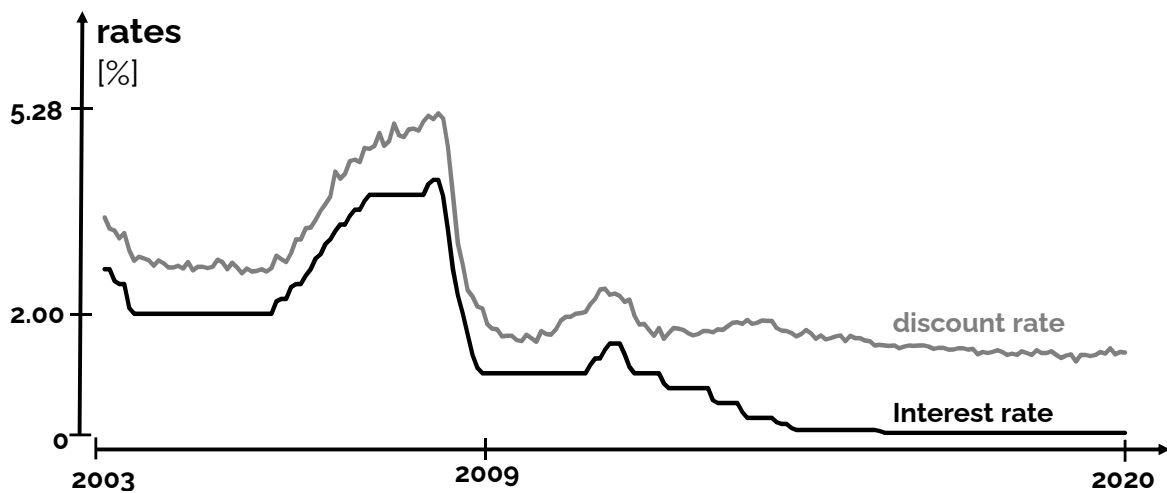


Figure C.5 – Comparison of Belgian interest rate and discount rate. The following rate was chosen to represent the discount rate: floating loans rate over a 1M€ (other than bank overdraft) and up to 1 year initial rate fixation.

For the different studies, the real discount rate for the public investor i_{rate} is fixed to 1.5%, which is similar to the floating loan rate over a million euros (other than bank overdraft) and greater than the central bank interest rate.

C.3 Technologies

The technologies are regrouped by their main output types.

C.3.1 Electricity production

The following technologies are regrouped into two categories depending on the resources used: renewable or not.

Renewables

Table C.5 – Renewable electricity production technologies, in 2035. Abbreviations: onshore (on.), offshore (off.).

	c_{inv} [€ ₂₀₁₅ /kW _e]	c_{maint} [€ ₂₀₁₅ /kW _e /y]	gwp_{constr} [kgCO ₂ -eq./kW _e]	Lifetime [y]	c_p [%]	f_{min} [GW]	f_{max} [GW]
Solar PV	870 ^a	18.8 ^a	2081 [113]	25 ^a [213]	11.9 ^b	0	59.2 ^d
On. Wind Turbine	1040 ^e	2.9 ^e	622.9 [113]	30 ^e [214]	24.3 ^b	0	10 ^f
Off. Wind Turbine	4975 ^g	9.8 ^e	622.9 [113]	30 ^e [214]	41.2 ^b	0	3.5 ^f
Hydro River	5045 [215]	50.44 [215]	1263 [113]	40 [215]	48.4	0.38 [216]	0.38 [216]
Geothermal ^h	7488 ^h	142 ^h	24.9 [113]	30	86 [218]	0	0 ⁱ

^aInvestment cost based on [94]. operation and maintenance (O&M) cost scaled proportionally based on IEA data.

^b Based on the real data of 2015 (data provided by ELIA, the Belgian TSO, which monitored 2952MW of PV, onshore and offshore in 2015^c).

^dAssuming that 250 km² of available roof well oriented exist today [101] and that the efficiency in 2035 will be 23% [94] with an average irradiation - similar to historical values - of 2820 Wh/m² in Belgium, [95]. The upper limit becomes 59.2 GW of installed capacity.

^e Onshore and offshore wind turbines in 2030 [94].

^f From previous study [99]

^gOffshore wind turbines in 2030 [94]. A correction factor of 2.58 is applied to have an LCOE of 79€/MWh in 2020, in line with recently published offer: <https://www.enerdata.net/publications/daily-energy-news/belgium-agrees-79mwh-lcoe-three-offshore-wind-parks.html>, visited on the 12-06-2020.

^hOrganic Rankine cycle (ORC) cycle at 6 km depth for electricity production. Based on Table 17 of [217]. We took the reference case in 2030.

ⁱA prototype (Balmatt project) started in 2019 and produces 4-5 MW [102]. However, the potential is not accurately known.

Data for the considered renewable electricity production technologies are listed in Table C.5, including the yearly capacity factor (c_p). As described in the Section 2.2.4, for seasonal renewables the capacity factor $c_{p,t}$ is defined for each time period. These capacity factors are represented in Figure C.6. For these technologies, c_p is the average of $c_{p,t}$. For all the other electricity supply technologies (renewable and non-renewable), $c_{p,t}$ is equal to the default value of 1. As the power delivered by the hydro river is almost negligible, we take the time series of hydro river from Switzerland [25].

Non-renewable electricity supply technologies

Data for the considered fossil electricity production technologies are listed in Table C.6. The maximum installed capacity (f_{max}) is set to a value high enough (100 000 TW_e) for each technology to potentially cover the entire demand.

Appendix C. Belgian energy system data in 2035

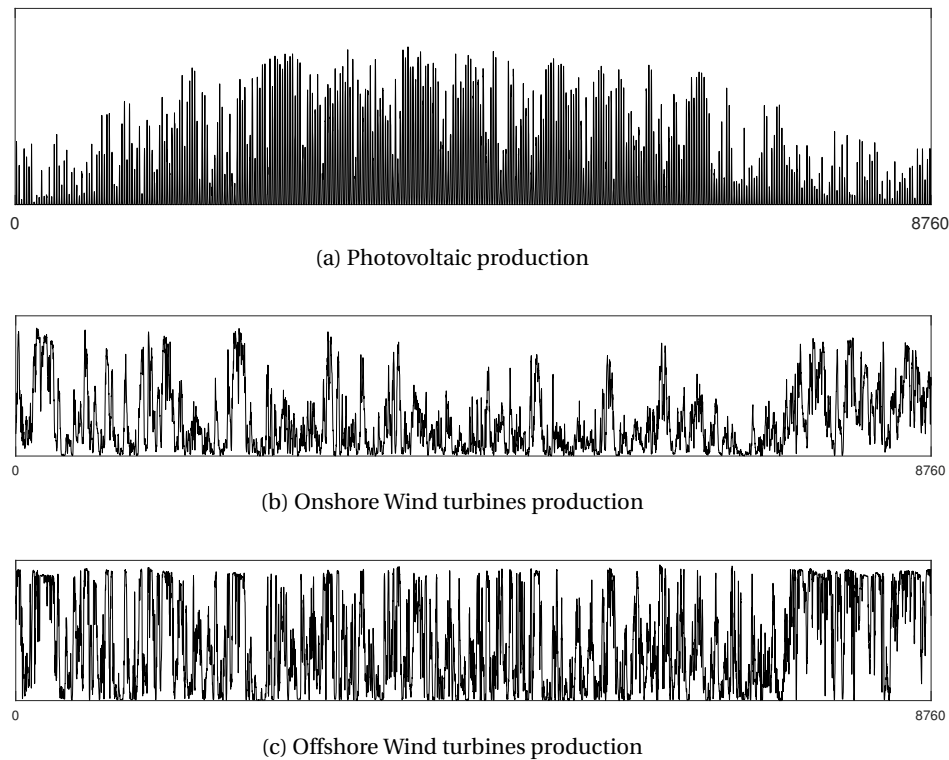


Figure C.6 – Capacity factor for the different renewable energy sources over the year.

Table C.6 – Non-renewable electricity supply technologies, in 2035. Abbreviations: combined cycle gas turbine (CCGT), ultra-supercritical (U-S), integrated gasification combined cycle (IGCC)

	c_{inv} [€ ₂₀₁₅ /kW _e]	c_{maint} [€ ₂₀₁₅ /kW _e /y]	gwp_{constr} [kgCO ₂ -eq./kW _e]	Lifetime [y]	c_p [%]	η_e [%]	$CO_{2direct}^a$ [tCO ₂ /MWh _e] ^a
Nuclear	4846 ^b	103 [219]	707.9 [113]	60 [221]	84.9 ^c	37	0
CCGT	772 [219]	20 [219]	183.8 [113]	25 [223]	85.0	63 ^d	0.317
U-S Coal	2517 ^e	30 ^e	331.6 ^f [113]	35 [223]	86.8 [223]	49 ^g	0.735
IGCC	3246 ^h	49 ^h		35 [223]	85.6 [223]	54 ⁱ	0.667

^aDirect emissions due to combustion. Expressed in ton CO₂ per MWh of electricity produced. Emissions computed based on resource used and specific emissions given in Table C.2.

^bInvestment cost: 3431 €₂₀₁₅/kW_e [219] + dismantling cost in Switzerland: 1415 €₂₀₁₅/kW_e [220].

^cData for the year 2012 [222]

^d0.4-0.5 GW_e CCGT in 2035 (realistic optimistic scenario) [223].

^e1.3 GW_e advanced pulverized coal power plant [224]. c_{maint} is fixed cost (29.2 €₂₀₁₅/kW_e/y) + variable cost (0.51 €₂₀₁₅/kW_e/y assuming 7600 h/y).

^fIn the lack of specific data, assuming same impact for coal power plants.

^gPulverized coal in 2025 (realistic optimistic scenario) [223].

^h1.2 GW_e IGCC power plant [224]. c_{maint} is fixed cost (48.1 €₂₀₁₅/kW_e/y) + variable cost (0.82 €₂₀₁₅/kW_e/y assuming 7500 h/y).

ⁱIGCC in 2025 (realistic optimistic scenario) [223].

C.3.2 Heating and cogeneration

Tables C.7, C.8 and C.9 detail the data for the considered industrial, centralized and decentralised CHP technologies, respectively. In some cases, it is assumed that industrial (Table C.7) and centralized (Table C.8) technologies are the same.

f_{min} and f_{max} for heating and CHP technologies are 0 and 100 TW_{th} , respectively. The latter value is high enough for each technology to supply the entire heat demand in its layer. the maximum ($f_{max,\%}$) and minimum ($f_{min,\%}$) shares are imposed to 0 and 100% respectively, i.e. they are not constraining the model.

Table C.7 – Industrial heating and cogeneration technologies, in 2035. Abbreviations: cogeneration of heat and power (CHP), electricity (Elec.), natural gas (NG).

	c_{inv} [€ ₂₀₁₅ /kW _{th}]	c_{maint} [€ ₂₀₁₅ /kW _{th} /y]	gwp_{constr} [kgCO ₂ -eq./kW _{th}]	Lifetime [y]	c_p [%]	η_e [%]	η_{th} [%]	$CO_{2,direct}^a$ [tCO ₂ /MWh _e] ^a
CHP NG	1408 ^b	92.6 ^c	1024 [113]	20 [223]	85	44 ^d	46 ^d	0.435
CHP Wood ^e	1080 [219]	40.5 [219]	165.3 [113]	25 [226]	85	18 [219]	53 [219]	0.735
CHP Waste	2928 ^f	111.3 ^f	647.8 ^g	25 [226]	85	20 [226]	45 [226]	0.578
Boiler NG	58.9[46]	1.2[46]	12.3 ^h	17 [227]	95	0	92.7[46]	0.216
Boiler Wood	115[46]	2.3[46]	28.9 [113]	17 [227]	90	0	86.4[46]	0.451
Boiler Oil	54.9 ⁱ	1.2 ^j	12.3 [113]	17 [227]	95	0	87.3[46]	0.309
Boiler Coal	115 ^k	2.3 ^k	48.2 [113]	17 [227]	90	0	82	0.439
Boiler Waste	115 ^k	2.3 ^k	28.9 ^l	17 [227]	90	0	82	0.317
Direct Elec.	332 ^m	1.5 ^m	1.47 [113]	15	95	0	100	0

^aDirect emissions due to combustion. Expressed in ton CO₂ per MWh of heat produced. Emissions computed based on resource used and specific emissions given in Table C.2.

^bCalculated as the average of investment costs for 50 kW_e and 100 kW_e internal combustion engine cogeneration systems [205].

^cCalculated as the average of investment costs for 50 kW_e and 100 kW_e internal combustion engine cogeneration systems [225].

^d 200 kW_e internal combustion engine cogeneration NG system, very optimistic scenario in 2035 [223].

^eBiomass cogeneration plant (medium size) in 2030-2035.

^f Biomass-waste-incineration CHP, 450 scenario in 2035 [219].

^gImpact of MSW incinerator in [46], using efficiencies reported in the table.

^h Assuming same impact as industrial oil boiler.

ⁱ925 kW_{th} oil boiler (GTU 530) [228]

^jAssumed to be equivalent to a NG boiler.

^k Assumed to be equivalent to a wood boiler.

^lAssuming same impact as industrial wood boiler.

^m Commercial/public small direct electric heating [229].

Figure C.7 represents the capacity factor ($c_{p,t}$) of solar thermal panels. The time series is the direct irradiation in Uccles in 2015, based on measurements of institut royal météorologique. For all the other heat supply technologies (renewable and non-renewable) $c_{p,t}$ is equal to the default value of 1.

Appendix C. Belgian energy system data in 2035

Table C.8 – District heating technologies, in 2035. Abbreviations: biomass (bio.), cogeneration of heat and power (CHP), digestion (dig.), hydrolysis (hydro.).

	c_{inv} [€ ₂₀₁₅ /kW _{th}]	c_{maint} [€ ₂₀₁₅ /kW _{th} /y]	gwp_{constr} [kgCO ₂ -eq./kW _{th}]	Lifetime [y]	c_p [%]	η_e [%]	η_{th} [%]	$CO_{2,direct}^a$ [tCO ₂ /MWh _e] ^a
HP	345 ^b	12.0 ^c	174.8 [113]	25	95	0	400	0
CHP NG	1254 ^d	37.5 ^d	490.9 ^e	25 [223]	85	50 ^f	40 ^f	0.500
CHP Wood ^g	1081 [219]	40.5	165.3	25 [226]	85	18 [219]	53 [219]	0.736
CHP Waste ^g	2928	111	647.8	25 [226]	85	20 [226]	45 [226]	0.578
CHP bio. dig.	1374 ^h	147.9 ^h	647.8 ⁱ	25 ^h	85 ^h	13 ^h	16 ^h	2.488
CHP bio. hydro.	4537 ^j	227	647.8 ^k	15	85	25.4	33.5	1.164
Boiler NG ^g	58.9[46]	1.2	12.3	17 [227]	95	0	92.7[46]	0.216
Boiler Wood ^g	115[46]	2.3[46]	28.9	17 [227]	90	0	86.4[46]	0.451
Boiler Oil ^g	54.9	1.2	12.3	17 [227]	95	0	87.3[46]	0.309
Geothermal ^l	1500 ^l	57.0 ^l	808.8[113]	30 ^l	85	0	100	0
Solar thermal ^m	362 ^m	0.43 ^m	221.8 [113]	30 ^m	10	0	100	0

^aDirect emissions due to combustion. Expressed in ton CO₂ per MWh of heat produced. Emissions computed based on resource used and specific emissions given in Table C.2.

^bCalculated with the equation: $c_{inv} [EUR_{2011}] = 3737.6 * E^{0.9}$, where E is the electric power (kW_e) of the compressor, assumed to be 2150 kW_e. Equation from [230], taking only the cost of the technology (without installation factor).

^cGround-water heat pump with 25 years lifetime [231].

^dCCGT with cogeneration [219].

^eImpact of NG CHP in from [46], using efficiencies reported in the table.

^f η_e and η_{th} at thermal peak load of a 200-250 MW_e CCGT plant, realistic optimistic scenario in 2035 [223].

^gAssumed same technology as for industrial heat and CHP (Table C.7)

^hCost estimations from [232] and efficiencies from [233]. Data in line with IEA: [234]

ⁱConstruction emissions is assimilated to an industrial CHP waste technology, presented in Table C.29.

^jOwn calculation

^kConstruction emissions is assimilated to an industrial CHP waste technology, presented in Table C.29.

^lGeothermal heat-only plant with steam driven absorption heat pump 70/17°C at 2.3 km depth (from [94]).

^mTotal system excluding thermal storage (from [94]).

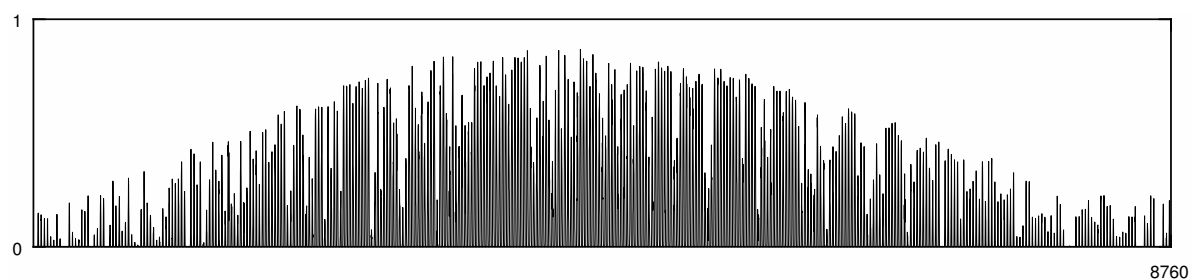


Figure C.7 – Capacity factor of thermal solar panels over the year.

Table C.9 – decentralised heating and cogeneration technologies, in 2035. Abbreviations: cogeneration of heat and power (CHP), electricity (Elec.), fuel cell (FC), heat pump (HP), natural gas (NG) and thermal (th.).

	c_{inv} [€ ₂₀₁₅ /kW _{th}]	c_{maint} [€ ₂₀₁₅ /kW _{th} /y]	gwp_{constr} [kgCO ₂ -eq./kW _{th}]	Lifetime [y]	c_p [%]	η_e [%]	η_{th} [%]
HP	492 ^{ab}	21 ^c	164.9 [113]	18 ^c	100	0	300
Thermal HP	316 ^{db}	9.5 ^e	381.9 [113]	20	100	0	150
CHP NG ^f	1408	92.6	1024	20 [223]	100	44	46
CHP Oil	1306 ^g	82.0 ^g	1024 ^h	20	100	39 ⁱ	43 ⁱ
FC NG	7242 ^j	144.8 ^k	2193 [113]	20 [238]	100	58 ^l	22 ^l
FC H ₂ ^m	7242	144.8	2193	20 [238]	100	58	22
Boiler NG	159[46]	5.08[46]	4.8[46]	17 [227]	100	0	90[46]
Boiler Wood	462 [239]	16 [239]	21.1 ⁿ	17 [227]	100	0	85 [239]
Boiler Oil	142 [228]	8.5 ^o	21.1[46]	17 [227]	100	0	85[46]
Solar Th.	719 ^p	8.1 ^q	221.2 [113]	20 [229]	11.3 ^r	0	-
Direct Elec.	40 ^s	0.18 ^t	1.47 [113]	15 [229]	100	0	100

^a10.9 kW_{th} Belaria compact IR heat pump [235].

^b Catalog data divided by 2.89. 2.89 is the ratio between Swiss catalog prices and prices found in the literature. Calculated by dividing the average price of a decentralised NG boiler (489 CHF₂₀₁₅/kW_{th}) in Swiss catalogs [236] by the price for the equivalent technology found in literature (169 CHF₂₀₁₅/kW_{th}, from [46]).

^c 6 kW_{th} air-water heat pump [229].

^d Specific investment cost for a 15.1 kW_{th} absorption heat pump (Vitosorp 200-F) [236]

^e 3% of c_{inv} (assumption).

^f Assumed same technology as for industrial CHP NG (Table C.7)

^g Assumed to be equivalent to a 100 kW_e internal combustion engine cogeneration NG system [205, 225].

^h Assuming same impact as decentralised NG CHP.

ⁱ Efficiency data for a 200 kW_e diesel engine [113]

^j System cost (including markup) for a 5 kW_e solid-oxide FC system, assuming an annual production of 50000 units [237].

^k 2% of the investment cost [219].

^l Solid-oxide FC coupled with a NG turbine, values for very optimistic scenario in 2025 [238].

^m Assumed to be equivalent to FC NG.

ⁿ Assuming same impact as NG and oil decentralised boilers.

^o 6% of c_{inv} , based on ratio between investment and O&M cost of boiler of similar size in [227].

^p 504 CHF₂₀₁₅/m² for the UltraSol Vertical 1V Hoval system [235]. For conversion from €₂₀₁₅/m² to €₂₀₁₅/kW_{th}, it is assumed an annual heat capacity factor of 6.5% based on Uccles data.

^q 1.1% of the investment cost, based on ratio investment-to-O&M cost in [229].

^r The calculation of the capacity factor for solar thermal is based on the IRM model [95] with radiation data from the city of Uccles, Belgium.

^s Resistance heaters with fan assisted air circulation in [227].

^t In the lack of specific data, same investment-to-O&M ratio as for direct electric heating in the industry sector (Table C.7).

C.3.3 Transport

Passenger mobility

The vehicles available for passenger mobility are regrouped in two categories: public and private. Private accounts for all the cars owned (or rented) by the user, such as a gasoline car, a diesel car... In opposition to private, public mobility accounts for the shared vehicles. It accounts for buses, coaches, trains, trams, metro and trolleys. From the literature, data about mobility is not directly transposable to the model. Data about mobility are usually given per vehicles, such as a vehicle cost or an average occupancy per vehicle. These data are summarised in Table C.10.

Table C.10 – Specific investment cost calculation based on vehicle investment data, in 2035. Abbreviations: average (av.), fuel cell (FC), hybrid electric vehicle (HEV), natural gas (NG), plug-in hybrid electric vehicle (PHEV), public (pub.).

Vehicle type	Veh. Cost [k€ ₂₀₁₅ /veh.]	Maintenance ^a [k€ ₂₀₁₅ /veh./y]	Occupancy [pass/veh.]	Av. distance [1000km/y]	Av. speed ^a [km/h]	Lifetime ^b [years]	gwp _{constr} [tCO ₂ /veh.]
Gasoline car	21 ^c	0.8	1.26 ^d	18 ^e	40	10	17.2
Diesel car	22 ^c	0.8	1.26 ^d	18 ^e	40	10	17.4
NG car	22 ^c	1.0	1.26 ^d	18 ^e	40	10	17.2
HEV car	22 ^c	0.5	1.26 ^d	18 ^e	40	10	26.2
PHEV car	23 ^c	0.5	1.26 ^d	18 ^e	40	10	26.2
BEV ^f	23 ^c	0.4	1.26 ^d	18 ^e	40	10	19.4
FC car	22 ^c	0.2	1.26 ^d	18 ^e	40	10	39.6
Tram and metro	2500	50.0	200	60	20	30	0 ^g
Diesel bus	220	11.0	24	39	15	15	0 ^g
Diesel HEV bus	300	12.0	24	39	15	15	0 ^g
NG bus	220	11.0	24	39	15	15	0 ^g
FC bus	375	11.3	24	39	15	15	0 ^g
Train pub.	10000	200.0	80	200	83	40	0 ^g

^aown calculation. The maintenance cost was assumed proportional to the investment cost and depending the type of powertrain. the average speed of private cars is calculated assuming that it is used 5% of the time (i.e. 1h12). Knowing the annual distance, the value is approximately 40 km/h.

^bIn 2016, the average age of private cars was 8.9 years with a difference between regions [240].

^c Costs are from mid-range vehicles estimation and projections of [124].

^d The federal bureau office estimates a decreasing average occupancy for cars down to 1.26 passenger/vehicle in 2030 [241]).

^e In 2016, averaged yearly distance for private cars were between 9 500 and 21 100 kms depending on the type of powertrains, but in average around 18 000 kms.

^fLow range battery electric vehicle (BEV) have been implemented. Otherwise the investment cost is more than twice.

^g No data found.

In Belgium, the car occupancy rate is less than 1.3 passengers per car: 1.3 in 2015 and estimated at 1.26 in [241]. The annual distance of a car depends on its type of motorization: from 9 500 km/year for a city gasoline car, to 21 100 km/year for a CNG one. On average, the distance is 18 000 km/year. The average age of a car is 8.9 years in 2016, with a variation between regions: in Brussels it is 10 years. On average, the distance is 18 000 km/year. The average age of a car is 8.9 years in 2016, with a rather strong variation between regions: in Brussels it is 10 years. Finally, a car drives on

average a slightly more than one hour a day (1h12). Although private car usage habits may change, we extrapolate these data from today to future years. Certain trends, such as the mutualisation of a car, could lead to an increase in the annual distance travelled by a car. But other trends, such as autonomous cars, could lead to a further decrease in the car occupancy rate, to values below 1. These change may influence in both direction the specific price of a kilometer passenger provided by a car.

For public transportation, the data were collected from various report [242–244]. These data have been adapted based on discussion with experts in the field. They are reported in table C.10

Surprisingly, in 2035, vehicles cost are similar regardless the power-train. Figure C.8 shows how the vehicle cost vary over the transition, data from [124]. Today, we verify a strong price difference between the different technologies, this difference will diminish with the development of new technologies. The price difference between two technologies will become small as early as 2035 ($\leq 10\%$). In their work, National Research Council [124] estimates the cost of promising technologies in 2015 lower than the real market price. This is the case for BEV and FC vehicles, where the price ranges today around 60 k€₂₀₁₅. These differences can be justified by three facts: these vehicles are usually more luxurious than others; The selling price do not represent the manufacturing cost for prototypes; the study is from 2013 and may have overestimated the production in 2015 and 2020.

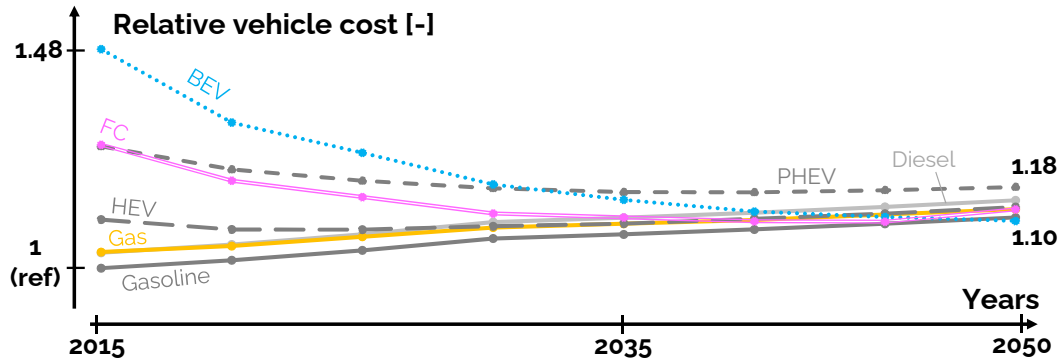


Figure C.8 – Mid-range vehicle costs evolution during the transition. Reference (**1.0 (ref)**) is at 19.7 k€₂₀₁₅. Abbreviations: Carbon capture (CC), light fuel oil (LFO), methanation (methan.), methanolation (methanol.), natural gas (NG), synthetic liquid fuel (SLF), synthetic natural gas (SNG), storage (sto.) and synthetic (syn.).

$$c_{inv}(i) = \frac{vehicle\ cost(i)}{Occupancy(i) \cdot average\ speed(i)} \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.2)$$

$$c_p(i) = \frac{average\ distance(i)}{average\ speed(i) \cdot 8760} \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.3)$$

$$veh.capa(i) = occupancy(i) \cdot average\ speed \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.4)$$

Appendix C. Belgian energy system data in 2035

From data of Table C.10, specific parameters for the model are deduced. The specific investment cost (c_{inv}) is calculated from the vehicle cost, its average speed and occupancy, Eq. C.2. The capacity factor (c_p) is calculated based on the ratio between yearly distance and average speed, Eq. C.3. The vehicle capacity is calculated based on the average occupancy and average speed, Eq. C.4. Table C.11 summarises these information for each passenger vehicle.

Table C.11 – Passenger mobility financial information, in 2035 (based on data in Table C.10). Abbreviations: fuel cell (FC), hybrid electric vehicle (HEV), natural gas (NG), plug-in hybrid electric vehicle (PHEV), public (pub.).

Vehicle type	c_{inv} [€/km-pass/h]	c_{maint} [€/km-pass/h/y]	gwp_{constr} [kgCO ₂ -eq./km-pass/h]	c_p [%]	veh_{capa} [(pass-km/h)/veh.]
Gasoline car	420	15.2	342	5.1	50
Diesel car	434	16.2	346	5.1	50
NG car	429	19.5	342	5.1	50
HEV car	429	9.9	519	5.1	50
PHEV car	456	10.5	519	5.1	50
BEV	450	7.7	385	5.1	50
FC car	435	3.0	786	5.1	50
Tram and metro	625	12.5	0 ^a	34.2	4000
Diesel bus	611	30.6	0 ^a	29.7	360
Diesel HEV bus	833	33.3	0 ^a	29.7	360
NG bus	611	30.6	0 ^a	29.7	360
FC bus	1042	31.3	0 ^a	29.7	360
Train pub.	1506	54.4	0 ^a	27.5	6640

^a No data found

Table C.12 summarises the forecast energy efficiencies for the different vehicles. For public vehicles in 2035, the energy efficiencies are calculated with a linear interpolation between the 2010 and 2050 values presented in Table 6 in Codina Gironès et al [149]. For private vehicles, Estimation for energy consumption for Belgium cars in 2030 are used [241].

The size of the BEV batteries is assumed to be the one from a Nissan Leaf (ZE0) (24 kWh⁷). The size of the PHEV batteries is assumed to be the one from Prius III Plug-in Hybrid (4.4 kWh⁸). The performances of BEV and PHEV batteries are assimilated to a Li-ion battery as presented in Table C.17.

Freight mobility

The technologies available for freight transport are trains, trucks and boats. Similarly to previous section, the information for the freight is given per vehicles. These data are summarised in table C.13.

⁷from https://en.wikipedia.org/wiki/Nissan_Leaf, consulted on 29-01-2019

⁸from https://fr.wikipedia.org/wiki/Toyota_Prius, consulted on 29-01-2019

Table C.12 – Fuel and electricity consumption for passenger mobility technologies in 2035 [149], and minimum/maximum shares allowed in the model. Abbreviations: fuel cell (FC), hybrid electric vehicle (HEV), natural gas (NG), plug-in hybrid electric vehicle (PHEV), public (pub.).

Vehicle type	Fuel [Wh/km-pass]	Electricity [Wh/km-pass]	$f_{min, \%}$ [%]	$f_{max, \%}$ [%]
Gasoline car	497 ^a	0	0	1
Diesel car	435 ^a	0	0	1
NG car	543 ^a	0	0	1
HEV ^b	336 ^a	0	0	1
PHEV ^c	138 ^a	109 ^a	0	1
BEV	0	173 ^a	0	1
FC car	264 ^d	0	0	1
Tram & Trolley	0	63 ^e	0	0.17 ^f
Diesel bus	265 ^d	0	0	1
Diesel HEV bus	198 ^d	0	0	1
NG bus	268 ^d	0	0	1
FC bus	225 ^d	0	0	1
Train pub.	0	65 ^e	0	0.60 ^f

^a calculation based on vehicle consumption in 2030 [241] and occupancy of 2030 [241]. According to [149], gas car are assumed to consume 25% more than diesel cars.

^bUsing gasoline as only fuel.

^cIt is assumed that electricity is used to cover 40% of the total distance and petrol to cover the remaining 60%.

^d In FC car are estimated to consume 52.6% more than BEV in 2035, see Table 2.12 in [124]

^eBased on real data for the French case in 2004, from [245]. An increase of efficiency of 25% was assume.

^fIn 2015, the public mobility was shared as follow: trains (37.0%), trams/metros (8.7%) and buses (54.3%) [92]. In 2035, we assume an upper limit twice greater than real data in 2015. Except for train were a maximum of 60% is imposed.

Table C.13 – Specific investment cost for freight vehicles, in 2035. Trucks data are from a report of 2019 [246]. Abbreviations: electric (elec.), fuel cell (FC) and natural gas (NG).

Vehicle type	Veh. Cost [k€ ₂₀₁₅ /veh.]	c_{maint}^a [k€ ₂₀₁₅ /veh./y]	Tonnage [tons/veh.]	Av. distance [1000km/y]	Av. speed ^a [km/h]	Lifetime [years]
Train freight ^a	4020	80.4	550	210	70	40
Boat Diesel ^a	2750	137.5	1200	30	30	40
Boat NG ^a	2750	137.5	1200	30	30	40
Truck Diesel	167	8.4	10	36.5 ^b	45	15
Truck FC	181	5.4	10	36.5	45	15
Truck Elec.	347	10.4	10	36.5	45	15
Truck NG	167	8.4	10	36.5	45	15

^aown calculation

^bIn 2016, the average distance was between 16 974 up to 63 305 km per year depending on the truck category. Based on our own calculation, we found an average of 36 500 km per year.

Appendix C. Belgian energy system data in 2035

Trucks have similar cost except for electric trucks. This last have a battery that supplies the same amount of kilometers than other technologies. As a consequence, half of the truck cost is related to the battery pack.

$$c_{inv} = \frac{vehicle\ cost(i)}{tonnage(i) \cdot average\ speed(i)} \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.5)$$

$$c_p = \frac{average\ distance(i)}{average\ speed(i) \cdot 8760} \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.6)$$

$$veh.capa(i) = Tonnage(i) \cdot average\ speed \quad \forall i \in TECHOFEUT(mob.pass) \quad (C.7)$$

From Table C.13, specific parameters for the model are deduced. Except for the technology construction specific GHG emissions (gwp_{constr}) where no data was found. The specific investment cost (c_{inv}) is calculated from the vehicle cost, its average speed and occupancy, Eq. C.5. The capacity factor (c_p) is calculated based on the ratio between yearly distance and average speed, Eq. C.6. The vehicle capacity is calculated based on the average occupancy and average speed, Eq. C.7. Table C.14 summarises these information for each freight vehicle.

Table C.14 – Freight mobility financial information, in 2035. Abbreviations: electric (elec.), fuel cell (FC) and natural gas (NG).

Vehicle type	c_{inv} [€ ₂₀₁₅ /km-t/h]	c_{maint} [€ ₂₀₁₅ /km-t/h/y]	c_p [%]	$veh.capa$ [t-km/h/veh.]
Train freight	104	2.1	34.2	38500.0
Boat Diesel	76	3.8	11.4	36000.0
Boat NG	76	3.8	11.4	36000.0
Truck Diesel	371	18.6	9.3	450.0
Truck FC	402	12.1	9.3	450.0
Truck Elec.	771	23.1	9.3	450.0
Truck NG	371	18.6	9.3	450.0

Trains and boats benefit on a very high tonnage capacity, and thus drastically reduce their specific investment cost down to 4-5 times lower than trucks. Table C.14 summarises the forecast energy efficiencies for the different vehicles in 2035. Except for the technology construction specific GHG emissions (gwp_{constr}) where no data was found.

Trains are considered to be only electric. Their efficiency in 2035 is 0.068 kWh/tkm [149]. The efficiency for freight transport by diesel truck is 0.51 kWh/tkm based on the weighted average of the efficiencies for the vehicle mix in [149]. For NG and H₂ trucks, no exact data were found. Hence, we assume that the efficiency ratio between NG coaches and diesel coaches can be used for freight (same for H₂ trucks). As a consequence, the efficiency of NG and H₂ trucks are 0.59 and 0.44 kWh/tkm. Boats are considered to be diesel or gas powered. In 2015, the energy intensity ratio

Table C.15 – Fuel and electricity consumption for freight mobility technologies, in 2035 [149]. Abbreviations: electric (elec.), fuel cell (FC) and natural gas (NG).

Vehicle type	Fuel [Wh/km-t]	Electricity [Wh/km-t]
Train freight	0	68
Boat Diesel	107 ^d	0
Boat NG	123 ^d	0
Truck Diesel	513 ^d	0
Truck FC	440 ^d	0
Truck Elec.	0	249 ^a
Truck NG ^b	590	0 ^f

^aEnergy intensity calculated based on the diesel one, and corrected with an electric to diesel powertrain ratio from [246].

^bThe efficiency is corrected with the ratio between NG bus and diesel bus.

between diesel boats and diesel trucks were $\approx 20\%$ ⁹. By assuming a similar ratio in 2035, we find an efficiency of 0.107 kWh/tkm and 0.123 kWh/tkm for diesel and gas boats, respectively.

C.3.4 Storage

Table C.16 and C.17 detail the data for the storage technologies. Table C.16 summarises the investment cost, GWP, lifetime and potential integration of the different technologies. Table C.17 summarises the technical performances of each technology.

The PHS in Belgium can be resumed to the Coe-Trois-Ponts hydroelectric power station. The characteristics of the station in 2015 are the following: installed capacity turbine (1164MW), pumping (1035MW), overall efficiency of 75%, all reservoirs capacity (5000 MWh). We assume that the energy losses is shared equally between the pumping and turbinning, resulting by a charge/discharge efficiencies of 86.6%. The energy to power ratio are 4h50 and 4h18 for charge and discharge, respectively [250]. A project started to increase the height of the reservoirs and thus increase the capacity by 425 MWh. In addition, the power capacity will be increase by 80MW. The overall project cost is estimated to 50M€ and includes also renovation of other parts¹⁰. We arbitrary assume that 50% is dedicated for the height increase. It results in an investment cost of 58.8€₂₀₁₅ per kWh of new capacity. The overall potential of the PHS could be extended by a third reservoir with an extra capacity of around 1.2 GWh. Hence, we assume that the upper limit of PHS capacity is 6.5 GWh. No upper bound were

⁹Value calculated based on the ratio between the transported tons and the consumed energy per technologies in 2015. Data from [89]

¹⁰This information was shared by Engie, the facility manager <https://corporate.engie-electrabel.be/projet-extension-centrale-coo/> and also publicised by newspapers: <https://www.renouvelle.be/fr/actualite-belgique/la-centrale-de-coo-augmente-sa-capacite-de-stockage>, <https://www.lameuse.be/403176/article/2019-06-20/va-agrandir-les-lacs-de-la-centrale-coo>.

Appendix C. Belgian energy system data in 2035

Table C.16 – Storage technologies characteristics in 2035: costs, emissions and lifetime. Abbreviations: batteries (batt.) battery electric vehicle (BEV), centralised (cen.), decentralised (dec.), Lithium-ions (Li-on), natural gas (NG), plug-in hybrid electric vehicle (PHEV), pumped hydro storage (PHS), seasonal (seas.), synthetic liquid fuel (SLF), temperature (temp.) and thermal storage (TS).

	c_{inv} [€ ₂₀₁₅ /kWh]	c_{maint} [€ ₂₀₁₅ /kWh/y]	gwp_{constr} [kgCO ₂ -eq./kW]	Lifetime [y]
Li-on batt.	302 ^a	0.62 ^a	61.3 ^b	15 ^c
PHS	58.8	0 ^d	8.33 ^e	50 ^f
TS dec.	19.0 ^g	0.13 ^g	0 ^d	25 ^g
TS seas. cen.	0.54 ^h	0.003 ^h	0 ^d	25 ^h
TS daily cen.	3 ^h	0.0086 ^d	0 ^d	40 ^g
TS high temp.	28	0.28	0	25
NG	0.051 ⁱ	1.3e-3 ⁱ	0 ^d	30 ⁱ
H ₂	6.19 ^j	3.0e-2 ^j	0 ^d	20 ^j
SLF	6.35e-3 ^k	3.97e-4 ^k	0 ^d	20 ^k
CO ₂ ^l	49.5 ^m	0.495 ^{lm}	0 ^d	20 ^l

^aWe assume a Lithium-ion NMC battery at a utility-scale in 2030 [115] with average use of 100 cycles/year.

^bData from Table 4 of [99].

^cTrade off between various sources: [115, 247]

^dNeglected.

^eOwn calculation based on Hydro Dams emissions from previous work [25, 46].

^fData verified in Table B1 of [247].

^gAdapted from Table 5.2 of [248].

^hThe technologies used are pit thermal energy storage technology and Large-scale hot water tanks for seasonal and daily DHN storage, respectively. Data was taken for year 2030 [115].

ⁱData from the Torup Lille project [115]. The lifetime is assumed similar to a cavern for hydrogen storage.

^jBased on tank storage from the JRC project[108]. The cost is assumed as the average of 2020 and 2050 costs.

^kIn 2013, the IEA estimated the facility storage cost to be between 8 and 37 USD/barril [249]. Taking the cheapest option, the investment cost is 6.35€₂₀₁₅/MWh. A similar methodology is applied to the operating and maintenance cost.

^lBased on liquid CO₂ tank storage. Data from a datasheet of *Ever grow gas* company <https://www.evergrowgas.com/>. Lifetime and maintenance cost based on own calculation.

^mUnits: **c_{inv}** [€₂₀₁₅/tCO₂], **c_{op}** [€₂₀₁₅/tCO₂/y]

constrained for other storage technologies.

Estimation for the gas storage is based on an existing facility using salt caverns as reservoirs: Lille Torup in Danemark [115]. The project cost is estimated to 254M€₂₀₁₅ for an energy capacity of 4965 GWh. The yearly operating cost is estimated to 6.5 M€₂₀₁₅. Part of it is for electricity and gas self consumption. We assume that the electricity is used for charging the system (compressing the gas) and the gas is used for heating up the gas during the discharge. These quantities slightly impact the charge and discharge efficiency of the system. The charge and discharge power are 2200 and 6600 [MW] respectively. As the technology is mature, we assume that the cost of the technology in 2035 will be similar to Lille Torup project.

Table C.17 – Storage technologies characteristics in 2035: efficiencies, energy to power ratios, losses and availabilities. Abbreviations: batteries (batt.) battery electric vehicle (BEV), centralised (cen.), decentralised (dec.), Lithium-ions (Li-on), natural gas (NG), plug-in hybrid electric vehicle (PHEV), pumped hydro storage (PHS), seasonal (seas.), synthetic liquid fuel (SLF), temperature (temp.) and thermal storage (TS).

	$\eta_{sto,in}$ [-]	$\eta_{sto,out}$ [-]	$t_{sto,in}$ [h]	$t_{sto,out}$ [h]	$\%sto_{loss}$ [s ⁻¹]	$\%sto_{avail}$ [-]
Li-on batt.	0.95 ^a	0.95 ^a	4 ^a	4 ^a	2e-4 ^{ab}	1
BEV batt.	0.95 ^a	0.95 ^a	4 ^c	10 ^c	2e-4 ^{ab}	0.2 ^c
PHEV batt.	0.95 ^a	0.95 ^a	4 ^c	10 ^c	2e-4 ^{ab}	0.2 ^c
PHS	0.866	0.866	4.30	4.83	0 ^d	1
TS dec.	1 ^d	1 ^d	4 ^c	4 ^c	82e-4 ^e	1
TS seas. cen.	1 ^f	1 ^f	150 ^f	150 ^f	6.06e-5 ^f	1
TS daily cen.	1 ^f	1 ^f	60.3 ^f	60.3 ^f	8.33e-3 ^f	1
TS high temp.	1 ^f	1 ^f	2	2	3.55e-4 ^f	1
NG	0.99 ^g	0.995 ^g	2256 ^g	752 ^g	0	1
H ₂	0.90 ^h	0.98 ^h	4 ^h	4 ^h	0	1
SLF ⁱ	1	1	1	1	0	1
CO ₂ ⁱ	1	1	1	1	0	1

^a Data verified in Table B1 of [247].

^b Data from Table 4 of [99].

^c Own calculation.

^d Neglected.

^e Adapted from Table 5.2 of [248]

^f Based on the Pit thermal energy storage technology in 2030 for seasonal and Large-scale hot water tanks for DHN daily storage. Data from [115].

^g Data from the Torup Lille project[115]. Efficiencies are based on our own calculation based on electricity and gas consumed by the installation over a year.

^h Sadaghiani and Mehrpooya [251] an efficiency of 88.6% in an ideal configuration for liquid hydrogen liquefaction. This high efficiency is used and we arbitrary impose that the charge efficiency is 90% and the discharge 98%. The tank design by JRC [108] has a charge/discharge energy to power ratio of 4 hours.

ⁱ We assume a perfect storage.

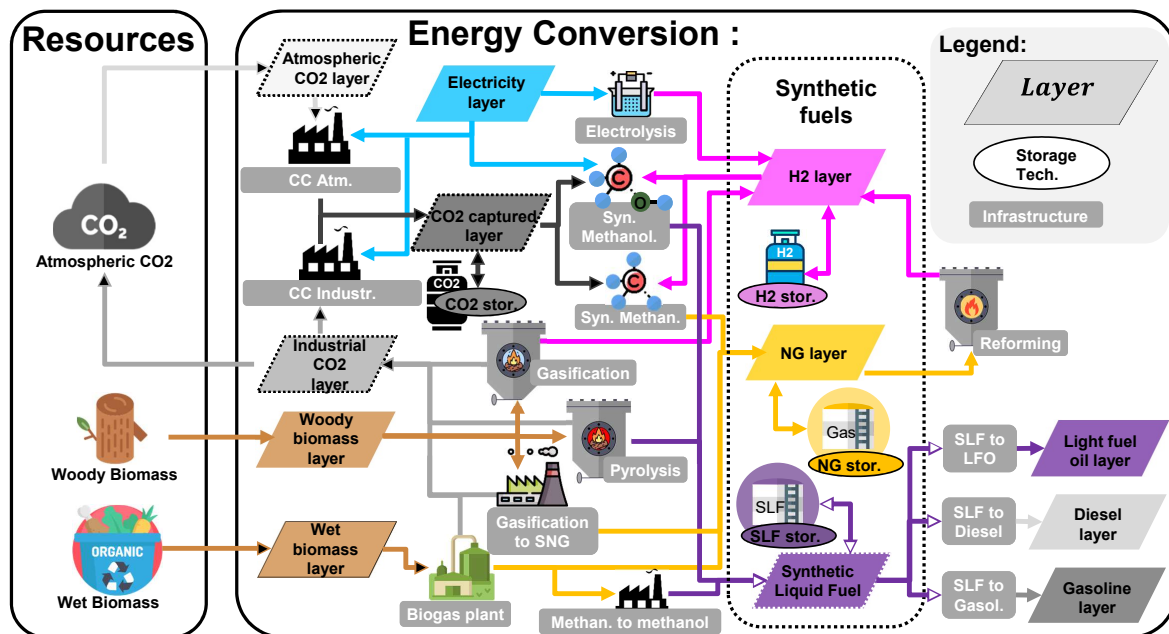


Figure C.9 – Illustration of the technologies and processes to produce synthetic fuels. For clarity, only the most relevant flows are drawn (Figure 4.1 includes all the flows).

C.3.5 Synthetic fuels production

Synthetic fuels are expected to play a key role to phase out fossil fuels [252]. Figure C.9 represents the technology related to synthetic fuels, including the carbon dioxide layers. Synthetic fuels can be imported (Bio-ethanol, Bio-Diesel, H₂ or SNG) or produced by converting biomass and/or electricity. The wet biomass - usually organic waste - can be converted through the *biogas plant* technology to SNG. This technology combines anaerobic digestion and cleaning processes. Woody biomass can be used to produce H₂ through *gasification*, or SLF through *pyrolysis* or SNG through *gasification to SNG*. The synthetic liquid fuel can later be converted into LFO, Gasoline or Diesel. The other processes to produce synthetic fuels are based on the water electrolysis, where the *electrolysers* convert electricity to H₂. Then, the H₂ can be combined with CO₂ and upgraded to SNG through the *methanation* technology. In this latter, the process requires CO₂. It can either be captured from large scale emitters, such as the industries and centralised heat technologies; or directly captured from the air but at a higher energetic and financial cost.

Hydrogen production

Three technologies are considered for hydrogen production: electrolysis, NG reforming and biomass gasification. The last two options can include carbon capture and storage (CCS) systems for limiting the CO₂ emissions. They are Different technologies for electrolysis, in their work the Danish Energy Agency [116] review the proton exchanger membrane electrolyser cell (PEM-EC), alkaline

electrolyser cell (A-EC) and solid oxide electrolyser cell (SO-EC). Table C.18 summarises the key characteristics for these technologies in year 2035.

Table C.18 – Characteristics of electrolyser technologies presented in [116], in 2035. Efficiencies are represent as follow: Input (negative) and outputs (positive). Abbreviations: temperature (temp.), high temperature (h.t.), low temperature (l.t.), electricity (e), hydrogen (H2).

	c_{inv} [€ ₂₀₁₅ /kW _{H2}]	c_{maint} [€ ₂₀₁₅ /kW _{H2} /y]	Lifetime [y]	η_e [%]	$\eta_{h.t.}$ [%]	η_{H2} [%]	$\eta_{l.t.}$ [%]
PEM-EC	870	40	15	-100		63	12
A-EC	806	43	25	-100		67	11
SO-EC	696	21	23	-85	-15	79	1.5

The different electrolyser cell technologies have a similar cost, however each technologies differ by their lifetime and electricity to hydrogen efficiencies. PEM-EC has the shortest lifetime and the lowest electricity to hydrogen efficiency, thus this technology will never be implemented in the model¹¹. Electrolysers will be needed during excesses of electricity production, where heat demand is usually low. Thus, they aim at maximising the production of hydrogen rather than low temperature heat. For this reason, SO-EC appear as the most promising technology SO-EC appears as the most promising technology and will be implemented in the model. Thus, in this work, the term *Electrolysis* refers to SO-EC. Table C.19 contains the data for the hydrogen production technologies.

Table C.19 – Hydrogen production technologies, in 2035.

	c_{inv} [€ ₂₀₁₅ /kW _{H2}]	c_{maint} [€ ₂₀₁₅ /kW _{H2} /y]	Lifetime [y]	c_p [%]	η_{H2} [%]	$CO_{2,direct}^a$ [tCO ₂ /MWh _e]
Electrolysis ^b [116]	696	21	23	90 ^c	79	0
NG reforming ^d [253]	681	64.4	25 ^c	86	73	0.273
Biomass gasification ^e [253]	2525	196	25 ^c	86	43	0.902

^aDirect emissions due to combustion. Expressed in ton CO₂ per MWh of fuel produced. Emissions computed based on resource used and specific emissions given in Table C.2.

^bIt uses electricity and high temperature heat as feedstock, see Table C.18

^c Own assumptions.

^dIt uses gas as feedstock, such as NG.

^eIt uses wood biomass as feedstock.

Hydrogen to other synthetic fuels

Two technologies can convert hydrogen to more advanced fuels and are summarised in Table C.20. Synthetic methanisation (*syn. methanisation*) and synthetic methanolation (*syn. methanolation*),

¹¹Not all the characteristics of the cell has been implemented, thus PEM-EC can be competitive compare to other technologies.

Appendix C. Belgian energy system data in 2035

which produce SNG and methanol (assimilated to SLF), respectively. This last can be freely converted to gasoline, diesel or LFO.

Biomass to synthetic fuels

Three technology options are considered for the conversion of biomass to synthetic fuels: pyrolysis, gasification and biomethanation. The main product of the pyrolysis process is bio-oil, which is considered equivalent to synthetic liquid fuel (SLF). The main product of the gasification and biomethanation processes are SNG, which is considered equivalent to fossil NG. Data for the technologies are reported in Table C.20 (from [46]). The biomethanation process is based on anaerobic digestion followed by a cleaning process in order to have gas that can be reinjected in the gas grid [116, 254]. In the table, efficiencies are calculated with respect to the wood in input (50% humidity, on a wet basis lower heating value (LHV)) and '*fuel*' stands for the main synthetic fuel in output.

Table C.20 – Synthetic fuels (except H₂) conversion technologies (from [46, 116] or specified), in 2035.

	c_{inv} [€ ₂₀₁₅ /kW _{fuel}]	c_{maint} [€ ₂₀₁₅ /kW _{fuel} /y]	Lifetime [y]	c_p [%]	η_{fuel} [%]	η_e [%]	η_{th} [%]	$CO_{2,direct}^a$ [tCO ₂ /MWh _e] ^a
Pyrolysis	1344	67.2	25	85	66.6	1.58	-	0.586
Gasification	2744	140	25	85	74	3.15	9.0	0.327
Biomethanation ^b	986	88	25	85	29.9	0	0	0.722
Hydrolysis methanation[255]	1592	112	15	100	42.3	0	4	0.306
Syn. methanation[256]	280	0.21	30	86	83.3	0	0	-0.198
Syn. methanolation ^c	1680	84	20	67	0	0	26.1	-0.248
Methane to methanol[258] ^d	958.6	47.9	20	1	65.4	0	0	0.306

^aDirect emissions due to combustion. Expressed in ton CO₂ per MWh of fuel produced. Emissions computed based on resource used and produced and specific emissions given in Table C.2.

^bCosts are adapted from [232] and technical data from [233].

^cData from [257] to produce 1 MWh of methanol, the process requires 1.355 MWh of hydrogen and also 0.04 MWh of electricity, 0.107 MWh of heating and 0.210 units of cooling. The process is simplified to 1.5 MWh of hydrogen needed to produce 1 MWh of methanol.

^dThis technology might be removed. Indeed, in this version of the model, synthetic liquid fuels are gathered together. However, they should be split in methanol, ethanol, bio-diesel... As a consequence, producing methanol from methane is cheaper than importing diesel. However in this version, methanol can be directly used as diesel → a competitor.

Carbon capture and storage

As represented in Figure C.9, two technologies are proposed to capture the CO₂, one from atmosphere (*CC Atmospheric*) and the other from exhaust gases of conversions processes (*CC industry*), such as after a coal power plant. Indeed, resources emit direct CO₂ from combustion and *CC industry* can concentrate CO₂ contained in the exhaust gas and inject it in CO₂ captured layer. The same process can be performed at a higher energetical cost with CO₂ from the atmosphere. No restriction

on the available limit of CO₂ from the atmosphere is considered. Data are summarised in Table C.21.

We suppose that *CC industry* has similar characteristics than a sequestration unit on a coal power plant as proposed in [94]. Based on our own calculation, we evaluated the economical and technical data. We assumed that the energy drop of the power plant represents the amount of energy that the sequestration unit consumes. We assume that this energy must be supplied by electricity.

For *CC atmospheric*, Keith et al. [259] proposed an installation where 1 ton of CO₂ is captured from the atmosphere with 1.3 kWh of natural gas and electricity. We assume that it can be done with 1.3 kWh of electricity. The thermodynamical limit is estimated to be around 0.2 kWh of energy to sequester this amount [260].

Table C.21 – Carbon capture (CC) technologies, in 2035. E_e represents the electricity required to capture sequester CO₂. η_{CO_2} represents the amount of CO₂ sequestered from the CO₂ source. Abbreviations: industrial (ind.), atmospheric (atm.).

	c_{inv} [€ ₂₀₁₅ /tCO ₂ -h]	c_{maint} [€ ₂₀₁₅ /tCO ₂ -h/y]	Lifetime [y]	E_e [kWh/tCO ₂]	η_{CO_2} [%]	$f_{min,\%}$ [%]	$f_{max,\%}$ [%]
CC Ind.	2580	64.8	40	0.233	90 ^a	0	100
CC Atm.	5160 ^b	129.6	40	1.3	100	0	100

^aWe consider that 10% of the CO₂ cannot be collected.

^bBased on the economical data given in [259] and own calculation.

No relevant data were found for the capacity factor (c_p) and the GWP associated to the unit construction.

C.3.6 Others

Electricity grid

No data were found for the Belgian grid. Hence, by assuming that the grid cost is proportional to the population, the Belgian grid cost can be estimated based on the known Swiss grid cost. In 2015, the population of Belgium and Switzerland were 11.25 and 8.24 millions, respectively (Eurostat). The replacement cost of the Swiss electricity grid is 58.6 billions CHF₂₀₁₅ [261] and its lifetime is 80 years [262]. The electricity grid will need additional investment depending on the penetration level of the decentralised and stochastic electricity production technologies. The needed investments are expected to be 2.5 billions CHF₂₀₁₅ for the high voltage grid and 9.4 billions CHF₂₀₁₅ for the medium and low voltage grid. This involves the deployment of 25GW of PV and 5.3 GW of wind onshore. These values correspond to the scenario 3 in [261]. The lifetime of these additional investments is also assumed to be 80 years.

By assuming a linear correlation between grid reinforcement and intermittent renewable deploy-

Appendix C. Belgian energy system data in 2035

ment, the specific cost of integration is estimated to 393 MCHF per GW of renewable intermittent energy installed $((9.4 + 2.5)\text{bCHF}/(25 + 5.3)\text{GW} = 0.393\text{bCHF/GW})$.

As a consequence, the estimated cost of the Belgian grid is $58.6/1.0679 \cdot 11.25/8.24 = 74.9 \text{ b€}_{2015}$. And the extra cost is $393/1.0679 \approx 367.8 \text{ M€}_{2015}/\text{GW}$.

Belgium is strongly interconnected to neighbouring countries. Based on an internal report of the TSO [263], the total transfer capacity (TTC) is estimated to be 6500 GW in 2020, which is in line with another study from EnergyVille [122] and the ENTSOE [114]. However, the net transfer capacity (NTC) published by the TSO on his website is much lower, around 3100 MW: 950 MW from Netherlands, 1800 MW from France and 350 MW from England (in 2020). This NTC is defined as ‘*The net transfer capacity (NTC) is the forecast transfer capacity agreed by Elia and its neighbouring transmission system operators (TSOs) for imports and exports across Belgium’s borders. [...] EU Regulation 543/2013 refers to net transmission capacity as ‘forecasted capacity’.*’¹². As explained in an internal report of the TSO [264], the total transfer capacity (TTC) is an upper bound of the NTC. In the literature, studies analysing the Belgium energy system accounts for the TTC, thus this capacity was implemented in this work: 6500 MW in 2020. The ENTSOE published his Ten Year Network Development Plan for different periods up to 2040. They estimates, if all projects are commissioned before 2035, the cross border capacities in 2035 up to 14 780 MW, which represents more than twice the available capacity in 2020 [114]. Figure C.10 illustrates the capacity changes for each neighbouring country, interconnections are reinforced in every countries more or less proportionally to the existing capacities.

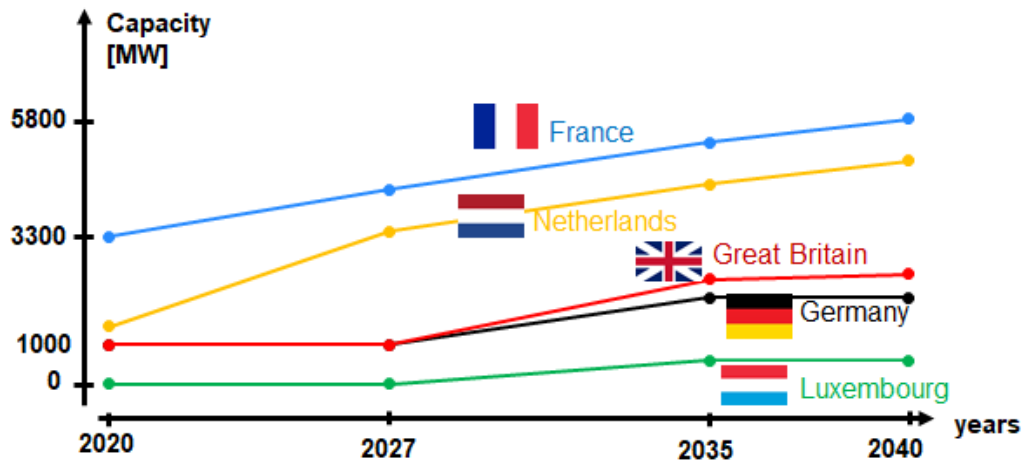
Losses ($\%_{net_{loss}}$) in the electricity grid are fixed to 4.7%. This is the ratio between the losses in the grid and the total annual electricity production in Belgium in 2016 [92].

In a study about “*electricity scenarios for Belgium towards 2050*”, the TSO estimates the overall import capacity up to 9.88 GW [100]. The interconnections are built as follow: 3.4 GW from Netherlands, 4.3 GW from France, 1.0 GW from Germany, 1.0 GW from Great Britain and 0.18 GW from Luxembourg¹³. However, a maximum simultaneous import capacity is fixed to 6.5 GW and justified as follow “*Additionally, the total maximum simultaneous import level for Belgium is capped at 6500 MW. For a relatively small country with big and roughly adequate neighbours, the simulations show that a variable import volume up to the maximum of 6500 MW can happen, thanks to the non-simultaneousness of peaks between the countries. But during certain hours, there is not enough generation capacity abroad due to simultaneous needs in two or more countries which will result in a lower import potential for Belgium. This effect is taken into account in the model*” [100]. The same ratio of simultaneous import and NTC (66%) is used for the other years.

¹²Information and definition from the TSO website: <https://www.elia.be/en/grid-data/transmission/yearly-capacity>, visited on the 29th of May 2020

¹³More details about capacities and projects are given in Figure 56 of [100].

Figure C.10 – Expected capacities between Belgium and neighbouring countries. Data from [114].



Losses ($\%_{netloss}$) in the electricity grid are fixed to 4.7%. This is the ratio between the losses in the grid and the total annual electricity production in Belgium in 2016 [92].

DHN grid

For the DHN, the investment for the network is also accounted for. The specific investment (c_{inv}) is 882 CHF₂₀₁₅/kW_{th} in Switzerland. This value is based on the mean value of all points in [265] (Figure 3.19), assuming a full load of 1535 hours per year (see table 4.25 in [265]). The lifetime of the DHN is expected to be 60 years. DHN losses are assumed to be 5%.

As no relevant data were found for Belgium, the DHN infrastructure cost of Switzerland was used. As a consequence, the investment cost (c_{inv}) is 825 €₂₀₁₅/kW_{th}. Based on the heat roadmap study [129], heat provided by DHN is “around 2% of the heating for the built environment (excluding for industry) today to at least 37% of the heating market in 2050”. Hence, the lower ($\%_{dhn,min}$) and upper bounds ($\%_{dhn,max}$) for the use of DHN are 2% and 37% of the annual low temperature heat demand, respectively.

Energy demand reduction cost

By replacing former device at the end user side, the end-use demand can be reduced. This is usually called an ‘energy efficiency’ measure. As an example, by insulating a house, the space heating demand can be reduced. However, energy efficiency has a cost which represents the extra cost to reduce the final energy needed to supply the same energy service. As in the model the demand reduction is fixed, hence the energy efficiency cost is fixed. The American Council for an Energy-Efficient Economy summarises study about the levelised cost of energy savings [266].

Appendix C. Belgian energy system data in 2035

They conclude that this cost is below 0.04 USD₂₀₁₄/kWh saved and around 0.024 USD₂₀₁₄/kWh, hence 0.018€₂₀₁₅/kWh. In 2015, Belgium final energy consumption was 415 TWh [2] and the energy efficiency around 15% compare to 1990. The European target is around 35% in 2035, hence the energy efficiency cost for Belgium between 2015 and 2035 is 3.32b€₂₀₁₅. This result is in line with another study for Switzerland where the energy efficiency cost is 1.8b€₂₀₁₅ for the same period and similar objectives [267] (see [46] for more details about Switzerland).

C.4 Real data in 2015 for model verification

The real energy system has been implemented for the passed year 2015. Thus, the following paragraphs present the different shares of technologies installed in that year, and it goes into more details as real data have been collected for that year.

This section details the data of the Belgian energy system in the year 2015 used to validate the LP model in Section 4.4.2. The input data for the year 2015 used for the model validation are: *i*) the yearly EUD values in the different sectors ($endUses_{year}$); *ii*) the relative annual production shares of the different technologies for each type of EUD; *iii*) the share of public mobility (%**Public**), of train and boat in freight (%**Rail**, %**Boat**) and of centralized heat production (%**Dhn**); *iv*) the fuel efficiency of mobility technologies.

The FEC data for Belgium in the year 2015 are available in [2, 89]. The EUD is calculated based on the FEC using a similar procedure as the one described in Section C.2.2. The obtained input data for model verification are reported in Table C.22. %**Public**, %**Rail**, %**Boat** and %**Dhn** are reported in Table C.23 with the corresponding sources.

Table C.22 – End-uses demand in Belgium ($endUses_{year}$) in 2015, calculated from [2, 89].

	Units	Households	Services	Industry	Transportation
Electricity (other)	[GWh]	20580	19703	31853	0
Lighting	[GWh]	806	4990	3855	0
Heat high T	[GWh]	0	0	69952	0
Heat low T (SH)	[GWh]	68463	34191	18194	0
Heat low T (HW)	[GWh]	17500	7665	4714	0
Passenger mobility	[Mpkm]	0	0	0	157551
Freight mobility	[Mtkm]	0	0	0	66000
Non energy	[GWh]	0	0	0	66306

The annual net electricity production shares for electricity production technologies is taken from [2, 92, 129] and summarised in Table C.24. The yearly shares of mobility and heating & CHP technologies per type of EUD (with respect to the main output) are reported in Tables C.25-C.29.

Table C.23 – %Public, %Rail and %Dhn for the Belgian energy system, in 2015.

	Share [%]
%Public	19.9% [92]
%Fr,Rail	10.9% [92]
%Fr,Boat	15.6% [92]
%Dhn	2% [129]

Table C.24 – Yearly production of electricity by technologies (in TWh of electricity). Data from [2, 92, 129]. The electricity imported is used to balance the yearly demand.

	Production [TWh _{elec.}]
Nuclear	24.34
CCGT	19.67
Coal	3.24 ^a
PV	3.376
Wind onshore	2.509
Wind offshore	2.5
Hydro	0.365

^aThere are no coal power plants in 2015. However, by using coal in industrial processes, gas furnaces are produced and sometimes used to produce electricity. It is estimated that 3.24 TWh/y is produced based on this process.

The report [92] is used to fix the different shares of mobility supplied for public mobility (Table C.25, [92]). For private mobility (Table C.26, [92]), it is assumed that all biofuels (≈ 3 TWh) is used for gasoline cars. The repartition between the different types of vehicles is estimated based on the number of vehicles in Belgium in 2015 (in millions: 2.11 gasoline, 3.46 diesel, 0.03 HEV, 0.02 NG and less for others) and their fuel efficiencies [127]. For all mobility technologies, 2010 efficiencies from [149] are used in the model verification.

For low and high temperature heat production (Tables C.27, C.28 and C.29, [92, 129]), the electricity production from CHP plants is taken from [89]), while the input fuel and the heat production are estimated based on the efficiencies assumed for 2035.

Eurostat reports the production of biogas to 229 ktoe in 2015, which represents 2.66 TWh of biogas [92]. Thus, the biogas production from biomethanation is imposed to this quantity.

C.5 Transition trends from 2015 to 2050

The technology related data are extrapolated for the different years based on trends. All the numerical values are available on the repository: [71]. Hereafter, some values and general trends are given.

Appendix C. Belgian energy system data in 2035

Table C.25 – Yearly shares of public mobility technologies for the Belgian energy system, in 2015. Data calculated based on Table 2.3.3 of [92].

	Share Mpkm [%]
Tram and Trolley Bus	4.5%
Diesel Bus and Coach	47% ^a
Diesel Hybrid Bus and Coach	0.0%
NG Bus and Coach	10.0% ^a
FC Bus and Coach	0.0%
Train/Metro	38.5%

^aBuses and coaches represent 57% of the public mobility. The split between both technologies was made based on our own calculation.

Table C.26 – Yearly shares of private mobility technologies for the Belgian energy system, in 2015. Data calculated based on Table 3.5 of [127].

	Share Mpkm [%]
Gasoline car	35.3%
Diesel car	63.7%
NG car	1.0% ^a
HEV	0.0%
PHEV	0.0%
BEV	0.0%
FC car	0.0%

^aNG car also accounts for LPG cars and thus is slightly overestimated.

Table C.27 – Yearly shares of decentralised low temperature heat & CHP technologies for the Belgian energy system, in 2015. Calculated based on [92, 129].

	Share heat [%]
HP	1.1%
Thermal HP	0.0%
CHP NG	0.7%
CHP Oil	0.0%
FC NG	0.0%
FC H ₂	0.0%
Boiler NG	39.6%
Boiler Wood	10.0%
Boiler Oil	48.4%
Solar Th.	0.2%
Direct Elec.	0.0%

Table C.28 – Yearly shares of DHN low temperature heat & CHP technologies for the Belgian energy system, in 2015. Calculated based on [92, 129].

	Share heat [%]
HP	4.4%
CHP NG	59.4%
CHP Wood	6.6%
CHP Waste	14.1%
Boiler NG	13.9%
Boiler Wood	0.0%
Boiler Oil	0.7%
Deep Geothermal	1%

Table C.29 – Yearly shares of industrial high temperature heat & CHP technologies for the Belgian energy system, in 2015. Calculated based on [92, 129].

	Share heat [%]
CHP NG	8.6%
CHP Wood	0%
CHP Waste	5.6%
Boiler NG	35.8%
Boiler Wood	0%
Boiler Oil	20.0%
Boiler Coal	30.0%
Boiler Waste	0%
Direct Elec.	0%

C.5.1 Resources and demand

Trends regarding the resources have already been discussed in Chapter 4 (see Section 4.1). Costs are given for several years (see Section 4.1.2), GWP are considered constant (see Section 4.1.3) and their availability is infinite, except for biomass and waste where the endogenous potential was taken (see 4.1.1).

Similarly, the EUD has been presented in Chapter 4 (see Section 4.2.1). The same methodology as the one presented previously (see Section C.2) has been used to adapt the projections of the European Commission [89] and compute future EUD.

C.5.2 Technologies

Capacity factors

All the technologies, except vehicles, have a high capacity factor (>85%) and undergoes a slight increase ($\leq 1\%$). The capacity factor of vehicles is driven by the amount of hours the vehicle is used during the day. It goes from a little bit more than 5% for a car up to 34% for trams and metro. As discussed in Section C.3.3, no clear direction is foreseen for the vehicles, and thus, the capacity are considered constant.

Investment costs

The investment cost have been given for the year 2035. In the following trends to adapt the data from 2035 have been collected from two sources: a study on vehicles for the transition for the investment costs [124] and the Danish Energy Agency for all the other technologies [94, 115, 116]. The trends are given in Tables C.30-C.33. The technologies can be regrouped into three categories: mature technologies, new technologies and others. The latter account for all technologies where data haven't been found. These technology can be split in ones which are similar to a technology where data have been found, such the cost trend of an oil boiler can be assimilated to the one of a gas boiler. And the technologies where no data have been found, which are nuclear, hydro, tramway, trains and daily thermal storage. For these no cost improvement are foreseen.

As previously noted in Part 4.3.1, some mature technologies will have a slightly increasing price. These include all vehicles with combustion engines. Other technologies will have a decrease in cost of about -6 to -13% of the price between 2015 and 2050, except the three following which will have a greater decrease: waste CHP (-19%), biomethanation (-23%) and steam methane reforming (-23%).

In the new technologies, we find those that are making great progress at present with a great drop in cost between now and 2035, then a less strong decrease, such as gasification to SNG, for example,

which has a yearly cost reduction of -7.7%/y between 2015 and 2035, then -0.3%/y between 2035 and 2050. There is also offshore wind energy (-2.7%/y then -0.5%/y), PV (-4.8%/y then -2.4%/y), pyrolysis (-7.0%/y then -2.9%/y), decentralised FC CHP (-4.3%/y and then -1.9%/y) and finally, the batteries (-8.6%/y and then -6.2%/y). The biggest cost drop is observed for hydrogen electrolyzers, where the cost before 2030 is very high. On the other hand, there are technologies that are declining at an accelerating rate, such as methanation, methanolation and CO₂ capture in industry. This delay can be explained by the low level of industrialisation of these technologies today and by the hopes placed in them. The other technologies have a cost decrease around 0.5-1%/y during the transition, they are: onshore wind, geothermal for electricity production, vehicles based on batteries and fuel cells, and HPs.

The last group of technologies are the one which are associated to another technology. There are 10 types of boilers which have a cost associated to a DHN gas boiler. There are 8 types of CHPs which are associated to waste or wood CHPs trends with a decrease cost below 1% every year. There are 4 types of freight vehicles based on combustion engines which are associated to buses based on combustion engines. There is the gasification of biomass to hydrogen which is associated to the gasification to SNG, the bio-hydrolysis methanisation which is associated to the bio-methanisation, the atmospheric CCS associated to the industrial one and the methane-to-methanol associated to the methanolation.

Table C.30 – Cost trends over the transition for electricity production technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Bold names account for several technologies. Abbreviations: combined cycle gas turbine (CCGT), electricity production (elec.), onshore (on.) and offshore (off.). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
PV	197%	140%	125%	109%	91%	82%	73%
Wind on.	130%	110%	106%	102%	98%	96%	94%
Wind off.	154%	108%	105%	102%	98%	96%	94%
Geothermal (elec.)	143%	117%	110%	102%	98%	95%	93%
CCGT	109%	107%	104%	101%	99%	98%	97%
Coal based Power plants	105%	103%	102%	101%	99%	98%	97%

Maintenance

The maintenance cost is calculated on the basis of the investments cost trends. The ratio of 2035, given in Section C.3, is assumed to be the same for all years.

Appendix C. Belgian energy system data in 2035

Table C.31 – Cost trends over the transition for heat production technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Bold names account for several technologies. Abbreviations: cogeneration of heat and power (CHP), decentralised (dec.), district heating network (DHN), electricity (elec.) and fuel cell (FC). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
Boilers	120%	120%	110%	100%	100%	100%	100%
Waste CHP	111%	109%	106%	103%	97%	94%	91%
FC dec. CHP	185%	127%	117%	107%	93%	85%	78%
Other CHP	109%	109%	105%	102%	98%	95%	93%
Industrial elec. Heating	117%	117%	108%	100%	100%	100%	100%
Geothermal (DHN)	107%	107%	104%	101%	99%	97%	96%
Solar thermal	109%	105%	103%	101%	99%	97%	96%
Dec. Direct elec.	109%	109%	105%	102%	98%	96%	95%
Heat pumps	122%	115%	109%	103%	97%	95%	92%

Table C.32 – Cost trends over the transition for vehicles. Bold names account for several technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Abbreviations: electricity (elec.), fuel cell (FC), plug-in hybrid electric vehicle (PHEV) and vehicles (veh.). Data from [243].

	2015	2020	2025	2030	2040	2045	2050
Veh. Diesel and Gasoline	93%	95%	97%	99%	101%	102%	103%
Veh. Hybrid	101%	99%	99%	99%	101%	102%	103%
Veh. Gas	95%	96%	98%	99%	101%	102%	103%
Car PHEV	108%	104%	102%	101%	100%	100%	101%
Veh. Elec.	127%	114%	108%	103%	98%	97%	97%
Veh. FC	114%	107%	104%	101%	99%	99%	101%

Table C.33 – Cost trends over the transition for synthetic fuels production and storage technologies. Bold names account for several technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Abbreviations: carbon capture and storage (CCS), steam methane reforming (SMR), synthetic (syn.) and thermal storage (TS). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
Electrolysers	0%	400%	255%	109%	91%	82%	73%
CCS technologies	111%	104%	102%	101%	99%	98%	96%
Syn. methanation	160%	133%	122%	111%	89%	77%	66%
Syn. methanolation	171%	158%	136%	114%	86%	71%	57%
Biomass gasification	254%	159%	130%	102%	98%	97%	95%
Pyrolysis	240%	190%	150%	110%	90%	80%	70%
Biomethanation/SMR	120%	114%	108%	102%	98%	95%	93%
TS seasonal	109%	109%	105%	101%	99%	97%	96%
Batteries	272%	166%	141%	116%	84%	68%	52%

Efficiencies

Similarly to previous paragraph, a study has been conducted on the evolutions of efficiencies based on the following sources: light duty vehicles for the vehicles efficiencies [243] and the Danish Energy Agency for all the other technologies [94, 115, 116]. The results are summarised in Tables C.34-C.37. For technologies with several outputs, the same improvement is assumed on each outputs. If a technology is not referenced, it means that efficiency is assumed constant over the transition.

Table C.34 – Efficiency trends over the transition for electricity production technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Bold names account for several technologies. Abbreviations: combined cycle gas turbine (CCGT). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
CCGT	94%	96%	98%	99%	101%	102%	102%
Coal based Power plants	88%	93%	96%	99%	101%	101%	102%

Table C.35 – Efficiency trends over the transition for heat production technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Bold names account for several technologies. Abbreviations: cogeneration of heat and power (CHP), decentralised (dec.), electricity (elec.) and fuel cell (FC). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
Boilers and CHP	99%	99%	100%	100%	100%	100%	100%
FC dec. CHP	90%	100%	100%	100%	100%	100%	100%
Industrial elec. Heating	99%	100%	100%	100%	100%	100%	100%
Dec. Direct elec.	99%	100%	100%	100%	100%	100%	100%
Heat pumps	90%	93%	95%	98%	102%	104%	106%

Table C.36 – Efficiency trends over the transition for vehicles. Bold names account for several technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Abbreviations: electricity (elec.), fuel cell (FC), plug-in hybrid electric vehicle (PHEV) and vehicles (veh.). Data from [124].

	2015	2020	2025	2030	2040	2045	2050
Veh. Diesel	88%	91%	94%	97%	103%	106%	109%
Veh. Hybrid	83%	87%	91%	96%	104%	109%	113%
Veh. Gasoline and Gas	86%	89%	93%	96%	104%	107%	111%
Car PHEV	84%	88%	92%	96%	104%	108%	112%
Veh. Elec.	85%	89%	93%	96%	104%	107%	111%
Veh. FC	76%	82%	88%	94%	106%	112%	118%

Appendix C. Belgian energy system data in 2035

Table C.37 – Efficiency trends over the transition for synthetic fuels production and storage technologies. Bold names account for several technologies. Reference year (100%) is 2035 where data is given in first Section C.3. Abbreviations: synthetic (syn.). Data from [94, 115, 116].

	2015	2020	2025	2030	2040	2045	2050
Electrolysers	86%	96%	98%	100%	100%	100%	100%
Syn. methanolation	95%	97%	98%	99%	101%	102%	103%
Biomass gasification	86%	93%	95%	97%	103%	105%	108%
Pyrolysis	99%	99%	99%	99%	101%	102%	103%
Batteries	99%	100%	100%	100%	100%	100%	100%

D Uncertainty characterisation and verification of parameters

Overview

- Uncertainty characterisation of parameters.
- Polynomial chaos expansion framework and formulation.
- Marginal cost of the demand.

The appendix is complementary to Section 6.2 of Chapter 6.

In any study involving uncertainty, from sensitivity to optimisation, the uncertainty of input parameters needs to be characterised, and a method to perform the uncertainty quantification must be selected. This Appendix presents the uncertainty characterisation performed, mainly based on Chapter 3 of the PhD thesis of [142] (Section D.1). Then, the polynomial chaos expansion (PCE) method used to perform the sensitivity analysis is presented (Section D.2). This method is applied to all parameters in order to identify a shorter list of influential ones. Indeed, a large number of parameter uncertainties have a negligible impact on the total cost of the system. Built on this shorter list, a global sensitivity analysis is performed in Chapter 6. Finally, independently from previous sections, a study was conducted to estimate the cost impact of changing the energy demand (Section D.3). By estimating the gradient of the total cost of the system around the annual demands, the marginal costs can be estimated for different scenarios.

D.1 Uncertainty characterisation

The characterisation of uncertainties is carried out in 2 phases. First, the parameters are identified and some of them can be grouped together or eliminated *a priori*. Then for each parameter or group of parameters, a method will be applied to estimate its uncertainty.

D.1.1 Preliminary screening and grouping

In this first phase, *all* model parameters are listed. This avoids an *a priori* arbitrary exclusion from the analysis. The preliminary screening consists of eliminating the parameters which are *certain* or *unused* or *redundant* by the model. A parameter is considered to be *certain* if it does not present any uncertainty (e.g. the number of hours in a day), if it is not related to the output of interest (e.g. GHG emissions specific to a technology construction in a cost optimization problem), or if it is imposed by the modeler to define the scenario (e.g. the share of renewables in the primary energy mix or the upper limit of GHG emissions). Other parameters have a negligible uncertainty and can thus be assumed certain for the model (e.g. the energy content of a fuel). A parameter is considered to be *unused* if the variable associated are never used, or the constraints never activated. As an example, private gasoline cars or boilers capacity factor. By optimising the total system cost, the private cars are never used as a similar technology has a higher efficiency: hybrid electric vehicle running also on gasoline. If the objective was different (e.g. total emissions), these technologies could be chosen. Boiler yearly capacity factors are close to 1, however, boilers are rarely used more than 50% of the time, so the constraints containing the boilers capacity factor are never activated. To estimate the unused parameters, the model has been evaluated for different scenarios with uncertain parameters. If a variable - mostly technology capacities - has never been activated, the associated parameters are qualified of unused.

Some of the remaining parameters are interdependent. For example, the price of diesel is generally correlated with the price of gasoline. When accounting for all the parameters, these prices are expected to be correlated and follow the same trend. Thus, their uncertainty can be linked to a same *hydrocarbon price* parameter. As this latter groups different parameters uncertainty, it is called a group of uncertain parameters. When the group uncertain parameter varies, it is assumed that all parameters vary in the same way. This way of grouping parameters cancels the effects associated with the interaction between parameters included in the same group.

By performing the preliminary screening and grouping, it results in 122 uncertain parameters. Among them, 18 are groups of parameters, such as the hydrocarbon prices, the electricity demands, etc.

D.1.2 Uncertainty characterisation results

In his work, Moret et al. [142], estimated the different range of uncertainties based on their characterisation, such as epistemic or aleatory, or even by analysing how the parameter's uncertainty could evolve over time. They summarise their work in a Table where 21 categories are proposed. Indeed, different uncertain parameters can be associated to the same category. As an example, two mature technologies may belong to the same category. Therefore, their range of uncertainty will be the same. Table D.1 summarises these categories. However, only 18 categories have been listed, the

three remaining are not used. This choice will be motivated in the following.

Table D.1 – Application of the uncertainty characterization method to the LP model. The 417 uncertain parameters are divided into 20 categories. Uncertainty is characterized for one representative parameter per category. The data used for the uncertainty characterization are reported in Appendix D.1. Abbreviations: district heating network (DHN), decentralized (DEC), electricity (elec), fuel cell (FC), industrial (I), natural gas (NG), photovoltaic (PV) and transport (TR).

Category	Representative Parameter	min	max
i_{rate}	i_{rate}	-46.2%	46.2%
$endUses_{year}(I)^a$	$endUses_{year}(I)$	-10.5%	5.9%
$endUses_{year}(TR)$	$endUses_{year}(TR)$	-3.4%	3.4%
$\eta_{mature,standard}$	$\eta(Boilers)$	-5.7%	5.7%
$\eta_{mature,customized}$	$\eta(GASOLINE\ CAR)$	-20.6%	20.6%
$\eta_{new,standard}$	$\eta(PV)$	-20.8%	20.8%
$\eta_{new,customized}$	$\eta(FC\ CAR)$	-28.7%	28.7%
$avail$	$avail(WOOD)$	-32.1%	32.1%
c_p	$c_p(NUCLEAR)$	-2.4%	2.4%
f_{max}	$f_{max}(PV)$	-24.1%	24.1%
$c_{inv,mature}$	$c_{inv}(DEC\ NG\ BOILER)$	-21.6%	21.6%
$c_{inv,new}$	$c_{inv}(PV)$	-39.6%	39.6%
	$c_{inv}(NUCLEAR)$	-21.6%	119.3%
	$c_{inv}(HYDRO\ DAM)^b$	-21.6%	73.8%
	$c_{inv}(Thermal\ plants)$	-21.6%	25.0%
$c_{inv,other}$	$c_{inv}(WIND)$	-21.6%	22.9%
	$c_{inv}(DHN)$	-39.3%	39.3%
	$c_{inv}(Geothermal)$	-39.7%	62.1%
c_{maint}	$c_{maint,\%}$	-48.2%	35.7%
$c_{op,local}$	$c_{op}(WOOD)$	-2.9%	2.9%
$c_{op,import}$	$c_{op}(NG)$	-47.3%	89.9%
$c_{p,t}$	$c_{p,t}(PV)$	-11.1%	11.1%
$\%_{loss}$	$\%_{loss}(Elec)$	-2.0%	2.0%

^aAs a conservative approach, this parameter was chosen among other similar ones because it has the largest range.

^bThis parameter is specific to the Swiss case. Thus it is used only for hydro dams in Belgium, which have secondary impact on the system cost.

Some choices had to be made to adapt Moret et al. [142] results to the current work. Indeed, in the case of the following parameters, the choice of category is not unique: new parameters and parameters specific to the case of Belgium. If a parameter could be associated with several categories, the one with the widest range was chosen. As an example, the efficiency of the synthetic methanation have been associated to the FC car efficiency rather than another which have a narrower range. As an exception, the uncertainty on the yearly demand has been defined differently. In [142], the demand was regrouped by sectors: households, services or industries. In our work, we assimilate the demand by type of end use type: electricity, heat low temperature etc...

The list of parameters included in [142] does not contain all the ones implemented in the thesis version of the model. Certain of these new parameters can easily be associated with categories of Table D.1, such as the uncertainty of the cost of a gas-powered truck which can be associated to a mature investment. However, other uncertainties cannot be classified, as they are specific to the Belgian case. It accounts for 9 parameters which can be gathered in three groups: (i) the upper bounds of mobility ($\%_{\text{public,max}}$, $\%_{\text{rail,max}}$, $\%_{\text{boat,max}}$) and the upper bound of heat that can be covered by district heating network ($\%_{\text{dhn,max}}$); (ii) the capacity of electrical interconnection with neighbours and the specific emissions of imported electricity; (iii) and finally, the maximum potential of geothermal and nuclear power. An arbitrary range of $\pm 10\%$ have been chosen for (i) and (ii). Things are different for the third group, the lower bound is 0 and the upper bound is the maximum capacity that could be installed. That is 5.6 GW for nuclear, 2 GW electric and 2 GW thermal for geothermal (data from 4.1.1).

D.2 Polynomial chaos expansion methodology and additional results

In the chapter 6, an overview of the methodology has been proposed (see Figure 6.4) without describing it in detail. In addition, an intermediate result allowing to reduce the number of parameters is mentioned without details. This section addresses these shortcomings by first showing the polynomial chaos expansion (PCE) methodology (i.e. mathematical formulation), and the additional result.

As a reminder, the same mathematical nomenclature is used: parameters in lower case and variables in bold.

D.2.1 Methodology

The PCE is a method to build a surrogate model, to propagate the uncertainty and quantify the Sobol's indices to perform a GSA [268]. The Sobol method decomposes the variance of the output of the model (system total cost) into fractions which can be attributed to inputs or a set of inputs. The PCE consists of a series of orthogonal polynomials Ψ_i with corresponding coefficients $\mathbf{y}_i$:

$$\hat{\mathbf{C}}_{\text{tot}}(\vec{\xi}) = \sum_{i=0}^P \mathbf{y}_i \Psi_i(\vec{\xi}) \approx \mathbf{C}_{\text{tot}}(\vec{\xi}) \quad (\text{D.1})$$

where $\vec{\xi} = (\xi_1, \xi_2, \dots, \xi_d)$ represents the vector of independent uncertain parameters and d is the number of uncertain parameters; $\mathbf{C}_{\text{tot}}$ and $\hat{\mathbf{C}}_{\text{tot}}$ are the total system cost estimation by EnergyScope TD model and surrogate model, respectively. If the series is infinite (i.e. $P = \infty$), it forms an exact representation of the system model, but its characterization is computationally intractable. Alternatively, a truncated series is defined, where the length of the truncated PCE depends on the

complexity of the relation between the stochastic inputs and objective, which is correlated with the order p of the polynomial, and the stochastic dimension d :

$$P + 1 = \frac{(p + d)!}{p!d!} \quad (\text{D.2})$$

Consequently, $P + 1$ coefficients $\mathbf{y}_i$ are present in the PCE. To quantify these coefficients, *least-square minimization* is applied, based on actual system model evaluations [138]. In order to ensure a well-posed *least-square minimization*, $2(P + 1)$ system model evaluations are usually required [138].

Statistical momentums

When the coefficients are quantified, the mean μ (Eq. (D.3)) and standard deviation σ (Eq. (D.4)) of the objective follow analytically :

$$\mu = \mathbf{y}_0 \quad (\text{D.3})$$

$$\sigma^2 = \sum_{i=1}^P \mathbf{y}_i^2 \quad (\text{D.4})$$

In addition to these statistical moments, the contribution of each stochastic parameter to the variance of the objective provides valuable information on the system behavior under uncertainty. Generally, this contribution is quantified through Sobol' indices. PCE provides an analytical solution to quantify these Sobol' indices through post-processing of the PCE coefficients (i.e. no additional model evaluations required). The total-order Sobol' indices ($S_i^{T,PC}$) are determined as:

$$S_i^{T,PC} = \sum_{\alpha \in A_i^T} \mathbf{y}_\alpha^2 / \sum_{i=1}^P \mathbf{y}_i^2 \quad |A_i^T = \{\alpha \in A | \alpha_i > 0\} \quad (\text{D.5})$$

where A is the set of all the PCE coefficients and α_i represents the coefficient related to uncertain parameter i .

Probability density function

As a second result, by using the surrogate model to perform a Monte-Carlo simulation, many more evaluations of the model can be performed in a little time. And thus the probability density function can be estimated for the objective function.

D.2.2 Results with the 122 parameters

Obtaining an accurate Sobol index requires to apply at least a 2nd order PCE. With the 122 parameters, it would require tens of thousands of evaluations. Whereas, applying the method with a 1st order would require only a few hundred evaluations. In a first step, we are interested in indexing

negligible parameters, i.e. those that have no impact on the total cost of the system. This will result in a shorter list that can be subjected to the higher-order method. To do this, the use of a first order Sobol's indices will allow to distinguish between parameters that have an influence and those that are negligible. Indeed, the choice can be binary, and the Sobol index value can be approximated. To increase the confidence of the result, this step is repeated five times. A parameter is qualified as *negligible* if its Sobol index value is close to 0 for all five cases. A result at high emissions is illustrated in Figure D.1.

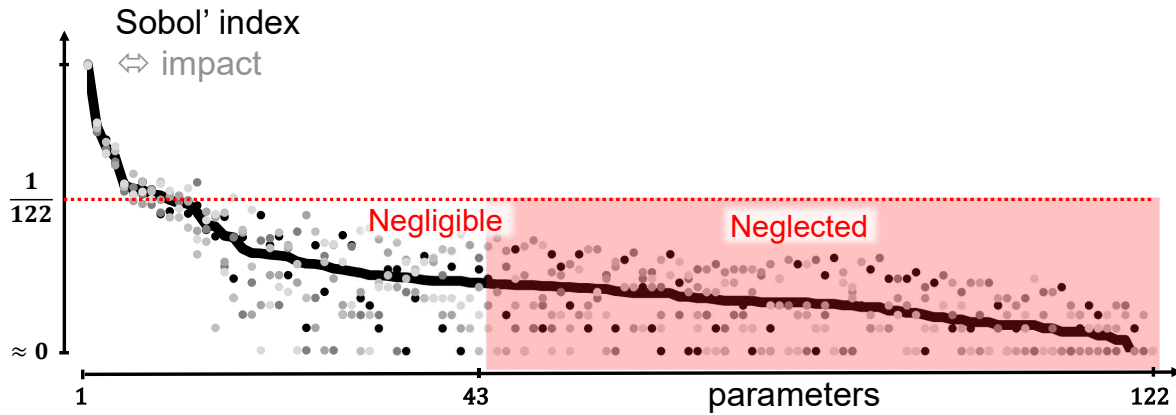


Figure D.1 – Illustrations of the five 1st order Sobol's indices for the 122 parameters (dots) and their mean (line). The y-axis is logarithmic. Only a dozen of parameters have at least one Sobol index greater than the threshold (red dot line). However, up to 43 parameters could be accounted in the second phase, and 79 of them will be neglected (shaded in red).

Figure D.1 shows that only a dozen parameters have a significant Sobol's indices for the five trials. Then, all the indices are negligible. A rule of good practice indicates that a parameter is negligible if its value is lower than the inverse of the number of parameters ($1/122 \approx 0.008$). As explained above, the value of the Sobol index is imprecise because it is based on an order one. This result is graphically represented by a wide range between dots of a same parameter (same column). As a result, the number of parameters chosen will be extended to 43. This number is chosen arbitrary to keep a tractable computational time. In the chapter 6, it is verified that the last chosen parameters are indeed negligible.

D.3 Marginal demand cost

If the price of energy drastically increases, will the consumers prefer to pay an increasing bill or to reduce their consumption? In other words, as a result of a market equilibrium, the cost of the system will have an influence on the yearly demand. This strategy isn't implemented in the model and thus not accounted in the studies. This limitation will be discuss in this section. The model could be extended to include an energy demand curtailment price, such as paying consumers $200\text{€}_{2015}/\text{MWh}$ if they don't consume electricity during critical hours. While this method has been successfully

implemented in the EnergyScope model (Master thesis work of John Morraine and Brieuc Bonnen [156]), imposing a curtailment price is highly speculative. Instead, by looking at the problem the other way around, the cost of an increase of the demand can be estimated. To achieve this, a local sensitivity analysis about the energy demand in 2050 is performed for different CO₂ emissions scenarios. The outcome of the analysis is the marginal cost of the energy demand, i.e. the cost ones will have to pay to consume one more unit of energy.

D.3.1 Methodology

As previously summarised in Section 2.2.4 (see Figure 2.8), there are eight different types of energy services. In a nutshell, energy services can be regrouped in four categories: electricity, heat, mobility and non-energy. The electricity has two components: a fixed demand over the year and a variable one. The heat demand is split into two temperature ranges: high temperature for industry processes and low temperature. The low temperature is also split in two parts: hot water for sanitary needs (constant over year) and space heating, which depends on a time series. Mobility encompasses the freight mobility and the passenger mobility. The non-energy demand has not been studied as motivated previously in Section 4.2.1.

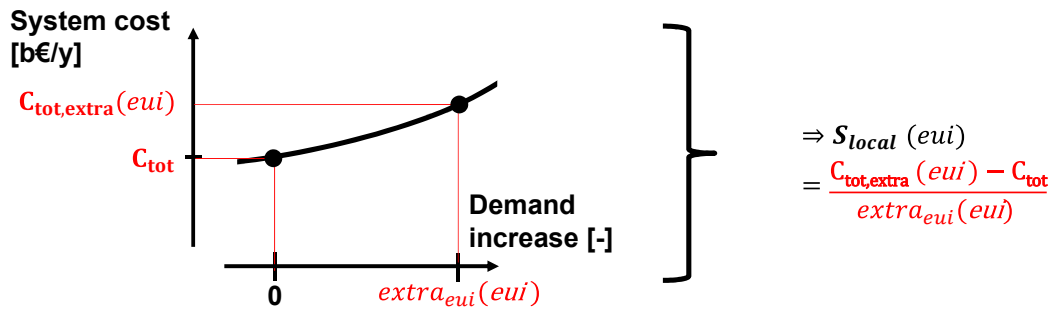


Figure D.2 – Method to estimate the local sensitivity (S_{local}) of an energy service, called *end use input* (eui). The model is evaluated for two cases: a reference scenario (**Ref.**) and a scenario where the energy service has been increased ($extra_{eui}$); for each case, the system costs are evaluated (C_{tot} and $C_{\text{tot,extra}}$, respectively). The local sensitivity (S_{local}) is defined as the gradient of the curve, i.e. the ratio between the cost increase and the demand increase.

$$\text{EndUsesInput}(eui) = \sum_{s \in \text{SECTORS}} \text{endUses}_{\text{year}}(eui, s) \cdot (1 + extra_{eui}(eui)) \quad \forall eui \in \text{END USE INPUT} \quad (\text{D.6})$$

$$S_{\text{local}}(eui) = (C_{\text{tot,extra}}(eui) - C_{\text{tot}}) / extra_{eui}(eui) \quad \forall eui \in \text{END USE INPUT} \quad (\text{D.7})$$

Demands are expressed in end use terms, such as kilometer-passenger for passenger mobility. These demands are calculated based on the different energy services also called *end use input*, given by sector. Figure D.2 illustrates how the local sensitivity (S_{local}) is calculated. To estimate the impact on the total cost of the system due to the increase in one of the energy services, the yearly end use input

Appendix D. Uncertainty characterisation and verification of parameters

is increased by an extra quantity ($extra_{eui}$) and just for one energy service, Eq. (D.6). Then, the model is evaluated and calculates a new total cost of the system ($C_{tot,extra}$). Finally, the local sensitivity of the energy service (S_{local}) is calculated as the ratio between the cost increase and the demand increase ($extra_{eui}$), Eq. (D.7). The cost increase is the difference between the new total system cost ($C_{tot,extra}$) and the reference one (C_{tot}).

By replicating this procedure to the different energy services, the marginal cost of a specific demand can be estimated. In other words, what would be the costs/savings to increase/decrease the energy demand. The parameter representing the extra demand ($extra_{eui}(eui)$) is arbitrary set to 1%.

D.3.2 Verification

In the previous methodology, two arbitrary assumptions were made: (i) demand is increased and (ii) a 1% increase is assumed for the energy service. The results might be different if demand had decreased or if a smaller amount of demand had been changed.

Consequently, the results obtained with the proposed method are compared with those obtained by modifying these assumptions. The latter results are obtained either by reducing demand (instead of increasing) or by modifying the magnitude of additional demand (instead of fixing it to 1%).

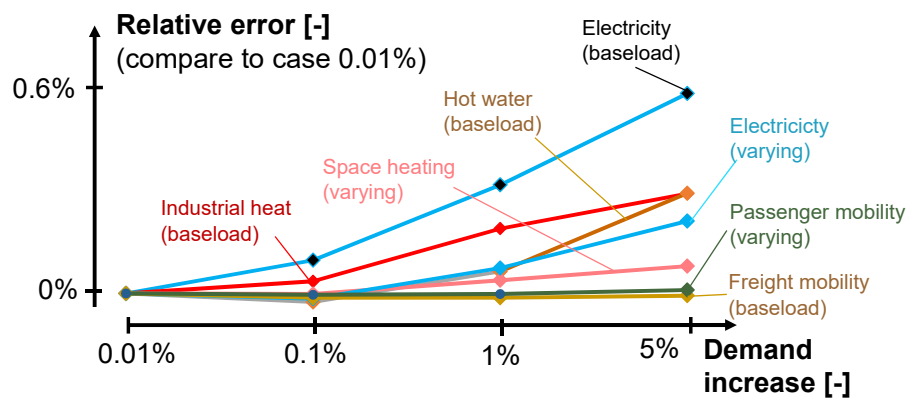


Figure D.3 – Relative error when using different extra demand magnitudes, for the low carbon scenario. Differences are negligible ($<0.6\%$).

Figures D.3 and D.4 show the results for the two tests. Figure D.3 represents the relative error compared to the smallest step size (0.01%) for the worst case studied, which is the carbon-neutral one. As shown in this figure, changing the step size has limited impact ($<0.6\%$). Figure D.4 gives the relative error when using a decrease demand, for different CO_2 emissions. This error is defined compared to the reference solution. As shown in the figure, it has little impact ($<1.24\%$) except with GHG emissions around 40 $MtCO_2/y$. At this level, the relative error is above 5%. As it will be explained later, the system moves from fossil to renewable fuels around 40 $MtCO_2/y$ implying a

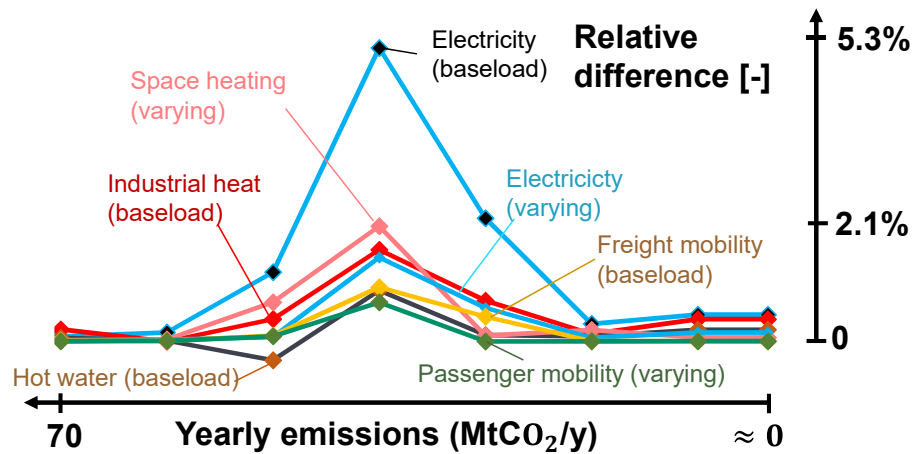


Figure D.4 – Relative error when decreasing the demand instead of increasing it.

significant cost increase.

In conclusion, using a 1% variation with a right side finite difference method appears as a consistent method.

D.3.3 Results

Figures D.5, D.6 and D.7 show the results for a demand change in electricity, heat and mobility services, respectively. These results are given for 2050, and for the carbon neutral scenario and compared to other scenarios where emissions are allowed. This choice is motivated to compare the low carbon scenario to scenarios where fossil fuels are allowed. Scenarios start at 70 MtCO₂, which is the cost optimum. Thus, at lower emissions, the system cost will increase as well as the marginal costs. Whatever the demand, reducing the system emissions implies a cost increase.

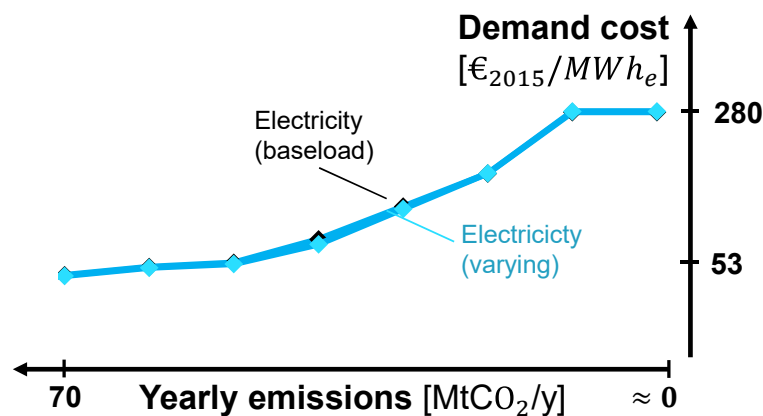


Figure D.5 – Marginal cost of electricity demand for different scenarios.

In the case of the electricity sector, the curve shape has three parts. First, the cost increases smoothly

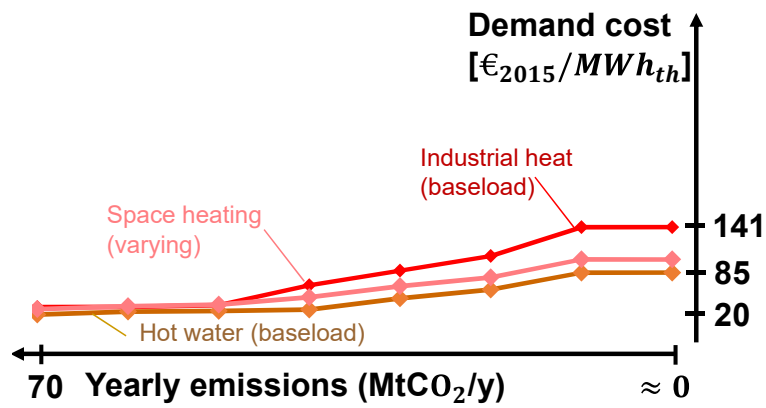


Figure D.6 – Marginal cost of heat demand for different scenarios.

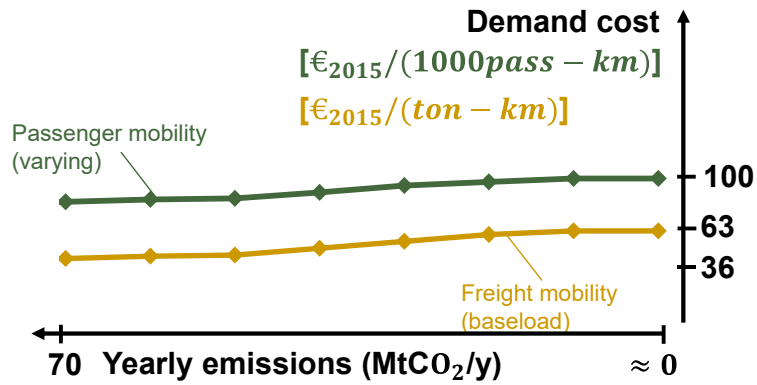


Figure D.7 – Marginal cost of mobility demand for different scenarios.

from 53 to 99 €/2015/MWh when emissions are decreasing from 70 to 50 MtCO₂/y. Second, the cost increases faster and up to 280 €/2015/MWh at 10 MtCO₂/y. Third, at lower emissions, the cost reaches a plateau. These three parts of the curve can be explained as it follows: first, electricity is produced by a mix of cheap renewable (LCOE ∈ [23-36] €/2015/MWh) and balanced by CCGT (LCOE=99 €/2015/MWh); then, more expensive renewable are deployed and solar becomes expensive to absorb; finally, using SNG instead of NG increases the CCGT LCOE from 99 up to 287 €/2015/MWh. This trend is followed by both energy service related to electricity: the base-load electricity demand and the varying component of the electricity demand.

The heat sector follows a similar trend. Indeed, as it is strongly electrified, an increase in the demand directly increases the electricity demand. The heat cost is cheaper than electricity cost. For low temperature heat - mainly based on heat pumps - the cost of heat is around 3-4 times cheaper than electricity. And indeed, the coefficient of performance (COP) of HP are between 3 and 4. Hot water is slightly cheaper as the demand is spread throughout the year. For high temperature heat, the system installs less CCGT and more industrial gas-CHP. The cost reflects the difference between the two solutions.

The mobility sector has a smoother and more constant growth. One will figure out that the scale is different (€/2015/(1000pass-km) or €/2015/(ton-km)) and thus, that numerical value cannot be directly compared to the other sectors. The cost is composed of two components: the technologies conversion costs and the resources costs. Mobility sector has a strong technology component costs, thus changing from cheap to more expensive fuels will have - compare to other sectors - a smaller impact on the passenger mobility cost (+30%) and freight mobility cost (+75%). These costs are consistent with the total cost of ownership (TCO) calculated in Section 4.3.3. The cost for extra passenger mobility is around 0.1€/2015/pass-km which is in between the TCO of public and private mobility.

D.3.4 Discussion

In 2018, the electricity averaged market price was 55 €/2015/MWh, in line with a production cost of the same magnitude at high emissions. This cost becomes six times greater in a low carbon society in 2050. Are industrial and citizens willing to pay electricity that is much more expensive? Will the demand be more elastic than today? Thus, reducing 1 MWh of electricity demand may be cheaper than paying 280 €/2015 for it. To emphasize, American Council for an Energy-Efficient Economy [266] estimated that, today, reducing energy demand costs between 13 and 40€/MWh.

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