UCLouvain

École polytechnique de Louvain

Pathway towards energy sustainability in Belgium under uncertainties

Author: **Benjamin Goffaux**
Supervisors: **Francesco Contino, Hervé Jeanmart**
Readers: **Xavier Rixhon, Thomas Pardoen**
Academic year 2020–2021
Master [120] in Mechanical Engineering

Abstract

This work analyses optimal pathways towards a sustainable energy system by 2050 in Belgium. The energy pathway model *EnergyScope Pathway* is used to optimise the Belgium energy transition. This work improved this model to start the transition from 2020 and model the transition more realistically. With this model, the optimal Belgium energy transition for four scenarios are analysed to understand how to transit towards energy sustainability and how Belgium could adapt in different contexts. For example, the nuclear phase-out in Belgium is analysed to understand how nuclear power plants could help the Belgium energy transition.

Another pathway model was developed in this work, *Simplified EnergyScope Pathway*, which is an accurate approximation of *EnergyScope Pathway* and is 5 times faster. This model is coupled with a polynomial chaos expansion (PCE) method in order to analyse the uncertainty on the Belgium energy transition. The mean and variance of the Belgium transition cost are computed to define the cost range to expect, and the uncertain parameters influencing the most the uncertainty of the Belgium energy transition are analysed.

A robust optimisation of the Belgium energy transition is then performed with a novel robust optimisation framework, presented in this work. This framework is used to identify some technologies that can make the Belgium energy transition more robust to uncertainties.

Acknowledgements

Firstly, I would like to thank Xavier Rixhon, my mentor in this master thesis, which was always there for me throughout this thesis. Thank you for giving me the best advices and feedbacks during this master thesis. Thank you also for always discussing my new ideas and results.

I would also like to express my gratitude to Professor Francesco Contino and Hervé Jeanmart, my promoters, for giving me the opportunity to work on such an interesting subject. I would also like to give a special thank you to Professor Contino for giving me great feedbacks throughout this academic year on how to properly present and write.

I would like to thank Gauthier Limpens for helping me with EnergyScope Pathway and for discussing some of my results.

I would also like to thank Diederik Coppiters for helping me with the polynomial chaos expansion method and giving me feedbacks on some results.

This master thesis would not have been possible without the weekly meeting with Xavier Rixhon, Denis Pinsar, Hadrien Planck, Antony Devresse and Guillaume André. Thank you to all of you.

My sincere gratitude also goes to Professor Thomas Pardoen for accepting to be one of my readers.

Last but not least, thank you to my family, my girlfriend and my friends for supporting me during this master thesis. This period was not easy with the current situation, but your support helped me during this entire academic year. Thank you also for the support during all these years at the EPL.

Contents

Acronyms

BEV battery electric vehicle.

CAPEX capital expenditure.

CCGT combined cycle gas turbine.

CHP cogeneration of heat and power.

DHN district heating network.

eHP electric heat pump.

EUD end-use demand.

FC fuel cell.

FEC final energy consumption.

GA genetic algorithm.

GHG greenhouse gas.

GSA global sensitivity analysis.

HEV hybrid electric vehicle.

HT high temperature.

IEH industrial electric heater.

LFO liquid fuel oil.

LHS latin hypercube sampling.

LOO leave-one-out.

LSA local sensitivity analysis.

LT low temperature.

MOEA multi-objective evolutionary algorithm.

NG natural gas.

NSGA-II nondominated sorting genetic algorithm II.

OPEX operational expenditure.

PCE polynomial chaos expansion.

PDF probability density function.

PHEV plug-in hybrid electric vehicle.

PHS pumped hydropower storage.

PV photovoltaic.

QoI quantity of interest.

SLF synthetic liquid fuel.

SMR steam methane reforming.

SNG synthetic natural gas.

thHP thermal heat pump.

TS thermal storage.

UQ uncertainty quantification.

V2G vehicle-to-grid.

Introduction

Climate change is one of the biggest problem humanity is facing nowadays. Dangerous consequences are foreseen for humanity if the global average temperature increases by 1.5-2°C compared to pre-industrial levels [1]. The major cause of climate change is the emissions of greenhouse gas (GHG). To face climate change, the Paris Agreement was negotiated in 2015 during the COP 21 in Paris. According to the UNFCCC website, *the Paris Agreement is a legally binding international treaty on climate change, adopted by 196 Parties. The goal of this agreement is to limit global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels. To achieve this long-term temperature goal, countries aim to reach global peaking of greenhouse gas emissions as soon as possible to achieve a climate neutral world by mid-century* [2]. The target for each country was set: reach carbon neutrality by 2050.

It is easier said than done. The transition towards carbon neutrality is a complex and complicated challenge. But one thing is sure, it comes with the change of our energy systems. Indeed, the principal source of GHG emissions is the consumption of fossil fuels. The issue today is that our energy systems are based on fossil fuels because they are cheap and convenient to use. In 2019, 84.3 % of the world primary energy supply was fossil fuels [3]. In Belgium, 79% of the gross available energy in 2018 was fossil fuels [4].

The goal of each country, that signed the Paris Agreement, is to transit towards a sustainable (i.e. carbon neutral) energy system by 2050. But the complicated part is how do we do that ? How do we substitute fossil fuels ? What technologies are the most interesting to reach this goal and when to deploy them ? How can we transit towards a sustainable energy system at the lowest cost ? To resume in a single question : *What is the optimal pathway towards energy sustainability ?* This master thesis aims at answering this question for Belgium, one of the 196 Parties that signed the Paris Agreement.

Energy pathway models exist to find the optimal energy transition towards energy sustainability. In their work, Prina et al. [5] reviewed the 'most established' models for long-term energy planning. They concluded that the existing models were limited in their applications, either by their heavy computational time, their poor time discretisation or the small number of sectors taken into account (only the electricity sector is covered). This motivated Gauthier Limpens to develop *EnergyScope Pathway*, a novel energy pathway model that does not feature the limitations of the other existing energy pathway models [6].

The first purpose of this master thesis is to understand how the Belgium energy system must change to achieve carbon neutrality. To do so, different Belgium transition scenarios will be presented and analysed using the EnergyScope Pathway model. The analysis of these transition scenarios will explain how to transit towards a sustainable energy system, what will be the keys for the Belgium transition, what technologies are the most interesting and when to deploy them. The transition scenarios analysis will also explain how nuclear power could help the Belgium energy transition, how Belgium can adapt if electricity can not be imported during the energy transition and how the politics could set a budget to realise this transition.

Moreover, the EnergyScope Pathway model is a deterministic model using perfect foresight. Perfect foresight means that the informations about the future (e.g. cost trends and energy demand forecasts) are assumed completely known by the decision-maker and must be given to the model. However, the world is full of uncertainties. The input parameters of the model are in fact uncertain. Uncertainties must be taken into account when analysing an energy transition, as it will be illustrated that the Belgium energy transition is strongly influenced by uncertainties. It is therefore important to analyse the uncertainty on the Belgium energy transition.

Uncertainties can be analysed in multiple ways. Uncertainty analysis can be performed to compute the mean and variance of the model output. A sensitivity analysis can also be performed to analyse the influence of an uncertain parameter on the output uncertainty. Two types of sensitivity analysis exist : a local sensitivity analysis (LSA) and a global sensitivity analysis (GSA). A LSA has a low computational time but hides the synergies between the parameter of interest and the others. On the contrary, a GSA has a higher computational time but takes into account the synergies between parameters. In his PhD thesis, S. Moret reviewed applications of sensitivity and uncertainty analysis methods to energy models [7]. Based on his review, he concluded that GSA methods are still limited in the energy field, mostly because of their high computational time. However, according to S. Moret [7], the synergies between the input parameters must be taken into account, in the case of an energy system, to perform a meaningful sensitivity analysis.

In this master thesis, an uncertainty quantification (UQ) method, known as the polynomial chaos expansion (PCE) method, will be used to perform an uncertainty analysis and a global sensitivity analysis, in an affordable time, on the Belgium energy transition. The purpose of this analysis is to compute the uncertainty range of the Belgium energy transition cost and identify what parameters are driving this uncertainty. The objective is also to prove that uncertainty analysis with an energy pathway model is affordable with methods like the PCE.

Furthermore, a true optimisation of the Belgium energy transition would not be complete without a robust optimisation. The best energy transition possible is a transition that minimises the total transition cost and is little influenced by uncertainties, to ensure that the total transition cost will not vary much from what was expected. Therefore, to find such an energy transition, a robust optimisation must be performed where both the mean and the variance of the total transition cost are minimised. However, robust optimisation applications with energy pathway models are actually scarce. The main reason might be that the computational time required is unaffordable with classic methods for robust optimisations.

In this master thesis, a novel robust optimisation framework is presented. The purpose of this framework is to perform a robust optimisation, affordable with energy pathway model, that takes into account uncertainties in every energy sectors and that considers the model as a black box. With this framework, a robust optimisation will be performed for the Belgium energy transition, over the whole energy system, to identify some technologies that can make the Belgium energy transition more robust.

This master thesis will be divided into 4 chapters. Chapter 1 will be focused on the functioning of the EnergyScope Pathway model and on a simplified version of this model that accurately approximates EnergyScope Pathway and is 5 times faster. Chapter 2 will be focused on the analysis of different energy transition scenarios for Belgium, to understand how to optimally transit towards a sustainable energy system by 2050 depending on the transition context (e.g. nuclear power phase-out or not). Chapter 3 will be focused on the uncertainty analysis of the Belgium energy transition to analyse the uncertainty of the transition cost and what drives it. Chapter 4 will be focused on the novel robust optimisation framework and its application on the Belgium energy transition to identify robust technologies. Afterwards, the results of this master thesis will be discussed and improvement ideas for future works will be given. Finally, the conclusion will summarise the results and accomplishments of this master thesis.

Chapter 1

Energy transition modelling

Energy models that represent an energy system over a year or any time period are widely used. In his PhD thesis [6], Gauthier Limpens compared the different existing energy models based on four criteria : is the model a multi-sectoral energy model (Electricity, heat and/or mobility) ? Does it optimise the cost or the operation of the energy system ? Is it open-source ? What is the computational time and is it acceptable for uncertainty analysis ? Based on his comparison, the existing energy models do not fully respect all the criteria. This is why, in his PhD thesis [6], Gauthier Limpens developed an energy model called EnergyScope Typical Days (EnergyScope TD) which respects the four criteria [6, 8]. It is multi-sector since it represents the electricity, the heat and the mobility sector, it optimises the hourly operation of the energy system, it is open-source[a] and the computational time is around 1 min which makes it suitable for uncertainty analysis.

Nevertheless, EnergyScope TD is an energy model that represents an energy system over a year. In order to model and optimise an energy transition, the model of interest should represent the energy transition and optimise its cost from today towards a sustainable (i.e. carbon neutral) energy system in a target year. The model must also verify that the energy system can operate during intermediary years to realistically model the energy transition.

Two methods can be applied to model a long-term energy planning. Either the model can evaluate the evolution of an energy system up to a target year, or it can use a one-year energy system modelling and couple it with another algorithm [6]. The first method is later called *'pathway'*, as in the PhD thesis of Gauthier Limpens [6], because it represents the energy system pathway from our current energy system to a sustainable one. In opposition, an energy model which represents the energy system in a target future year (i.e. a one-year energy model) can be called a *snapshot* model according to Gironès et al. [9]. For example, EnergyScope TD is a snapshot model because it optimises only one year and does not take into account the energy transition from today to the energy system of that target year.

In their work, Prina et al. [5] reviewed the 'most established' models for long-term energy planning. The different models were analysed through different criteria : the time horizon, the time step, the energy sectors covered, the objective function, the model approach and the computational time. The reviewed pathway models featured at least one of the following limitations : heavy computational burden, poor time discretisation and/or only electricity sector covered. Consequently, Prina et al. decided to follow the second method to create a long-term energy planning model. They coupled a snapshot model with low computational time to a multi-objective evolutionary algorithm (MOEA) that optimises both the cumulated cost and the CO_2 emissions of the energy system during the transition.

However, the long-term energy planning model of Prina et al. does not optimise the full energy system design

[a]Repository : `https://github.com/energyscope/EnergyScope/tree/v2.0`

and the hourly operation. The only decision variables of the MOEA are the installed capacity of photovoltaic panels, of onshore wind turbines and of batteries. Moreover, the code of their method is not open-source. Therefore, there was a need for an energy transition model that respects the criteria stated earlier.

Consequently, Gauthier Limpens extended the EnergyScope TD model into a pathway model, called *EnergyScope Pathway*, that respects all the criteria. This model minimises the total transition cost by optimising the installed capacity and the hourly operation of the energy system during eight representative years of the transition. Moreover, it is open-source[b] and has a computational time of around 30 mins[c]. EnergyScope Pathway is the model used in this master thesis to model and analyse the transition of the Belgium energy system towards a sustainable energy system. Furthermore, some features were added to the model to add realism to the energy transition.

This chapter will first explain, in section 1.1, how the EnergyScope TD model works since this model is the starting point to understand the EnergyScope Pathway. Then, in section 1.2, the EnergyScope Pathway model will be explained and the improvements brought to the model will be detailed to complement the description of the EnergyScope Pathway in Gauthier Limpens PhD thesis [6]. Finally, in section 1.3, a simplified version of the EnergyScope Pathway model, called *Simplified EnergyScope Pathway*, will be presented. This model approximates accurately the EnergyScope Pathway model while being 5 times faster.

1.1 EnergyScope TD

EnergyScope TD is a simplified representation of an energy system. Three energy sectors are taken into account : electricity, heat and mobility. The heat sector is divided into three sub-sectors : high temperature heat for industries, low temperature heat for hot water and low temperature heat for space heating. The mobility sector is divided into two sub-sectors : freight and passenger mobility.

Each sector/sub-sector has an end-use demand that must be met during each hour of a year. The demands must be known and given in terms of end-use demand (EUD) instead of final energy consumption (FEC). The link between the two is that the FEC is the energy input needed in order to satisfy the EUD. For example, a combined cycle gas turbine (CCGT) consumes natural gas (NG) to produce electricity. The EUD is the electricity requested by the consumer while the FEC is the NG required by the CCGT to produce this electricity.

The energy system contains three layers : the resources, the energy conversion technologies and the demands. An illustration of those three layers in an energy system is shown in Figure 1.1. Basically, resources are used by conversion technologies to produce the end-use energies. Let's take the example above, natural gas (NG) is a resource that can be used in a CCGT, which is the converting technology, to produce electricity in order to supply the electricity demand. Nevertheless, the system can be more sophisticated than just one resource used in one conversion technology to supply one demand. For example, a CCGT can produce electricity, not for the electricity demand but as a resource for an electric heat pump that will produce low temperature heat, or the electricity can be stored in a battery to be used later.

Moreover, EnergyScope TD contains 20 resources, 85 technologies and 8 end-use demand types. All of these are represented in Figure 1.2 with their inputs and outputs. The technologies taken into account are either technologies used today or new technologies with interesting potential.

[b] Can be found at `https://github.com/energyscope`

[c] With the AMPL algebraic modelling system and optimisation. More informations about AMPL at : `https://ampl.com`

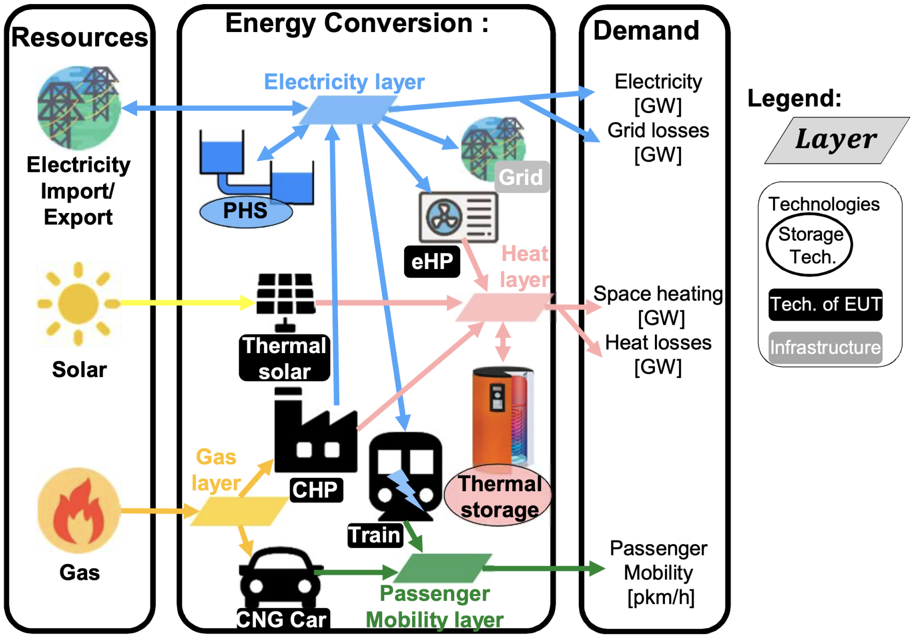

Figure 1.1: Example of the three different layers of the EnergyScope TD model. Resources are used in conversion technologies to produce another type of energy that will be used either to meet the demand, to be consumed by another technology or to be stored. This Figure comes from the article of G. Limpens, et al., on the EnergyScope TD model [8]. Abbreviations: pumped hydropower storage (PHS), electric heat pump (eHP), cogeneration of heat and power (CHP), compressed natural gas (CNG).

Mathematically, the EnergyScope TD model is formulated as a linear programming (LP) problem, optimised by an optimisation algorithm [6]. The model requires the following **input parameters**:

<u>Resources, technologies and end-use demands</u>

- Price, maintenance cost and efficiency of the technologies
- Greenhouse gas (GHG) emissions related to the technologies construction
- Price an availability of the resources
- GHG emissions related to the resources consumption
- End-use demands (EUDs)

<u>To constrain the energy system and add realism</u>

- Technologies minimum and maximum installed capacity
- Minimum and maximum share between public and private mobility. It prevents the energy system to use, for example, only public mobility for passenger mobility which will be unrealistic.
- The minimum and maximum share between the train, the boat and the road for the freight mobility.
- The minimum and maximum share between district heating network (DHN) and decentralised low temperature heat.

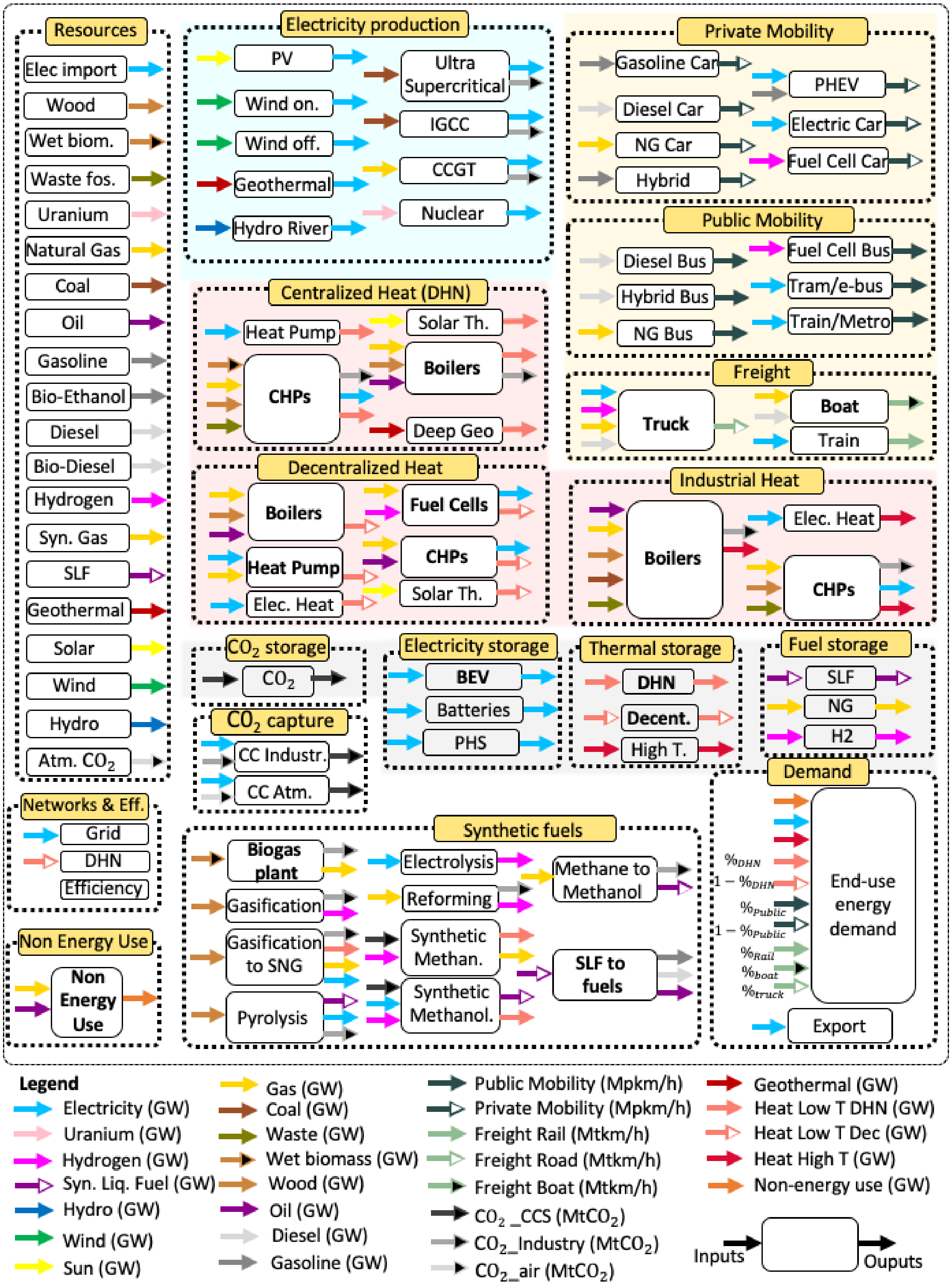

Figure 1.2: Resources, technologies and demands implemented in the EnergyScope TD model. The technologies in **bold** represent a type of technology that can use different resources (e.g. **Boilers** includes gas boilers, wood boilers, ...). **Decent** represent the different thermal storage associated with their corresponding decentralised heat production technology (e.g. **Decent** contains a decentralized gas boiler storage that can store the heat produce by a decentralised gas boiler).

Others

- Investment cost annualisation factor
- Real discount rate
- Times series discussed below
- GHG emissions limit forcing the system to emit less GHG emissions
- ...

The exhaustive list of the input parameters can be found in the documentation of EnergyScope TD [10] or in the PhD thesis of Gauthier Limpens [6].

After the input parameters have been given to the model, the **optimisation** of the energy system over the year can start. The objective function (i.e. the variable to optimise) can either be the total cost of the system over the year, or the GHG emissions over the year. The decision variables (i.e. the values the optimiser can change) are the installed capacity of technologies and the hourly system operation. The purpose of the optimisation algorithm is to find the decision variables that minimise the objective function while respecting the constraints (the end-use demands must be met every hour, ...).

When this system is found, the **outputs** of the model are saved. The outputs are the total cost of the system (total cost of resources, total investment cost of technologies, ...), the GHG emitted by the energy system, the installed capacity of technologies and the hourly energy system operation.

Furthermore, the TD in EnergyScope TD stands for Typical Days. Instead of simulating 365 days independently, 12 typical days are used to represent every day of the year. This decreases dramatically the computational time, as explained in the article of G. Limpens et al. [8]. In this article, G. Limpens et al. demonstrate that the optimal number of typical days is 12. In the 12 typical days, some are sunny, some are cloudly, some are warm and some are cold. Those typical days are distributed over the year to simulate realistically a whole year. For example, there will be more warm days in the summer than in the winter.

The intermittent nature of renewable energy is modelled by time series during each typical day. As an example, the time series of photovoltaic (PV) panels represent the electricity that PV panels will produce in a given hour of a typical day. The time series are coherent with the typical days as PV panels will not produce electricity during the night and more electricity will be produced during a sunny day than a cloudy day.

There are also time series for some EUDs: the space heating, the electricity used for lighting and the passenger mobility. As an example, the time series used for space heating is represented in Figure 1.3. The demand for space heating is bigger during the winter than during the summer which illustrates the coherence in the repartition of the typical days during the year.

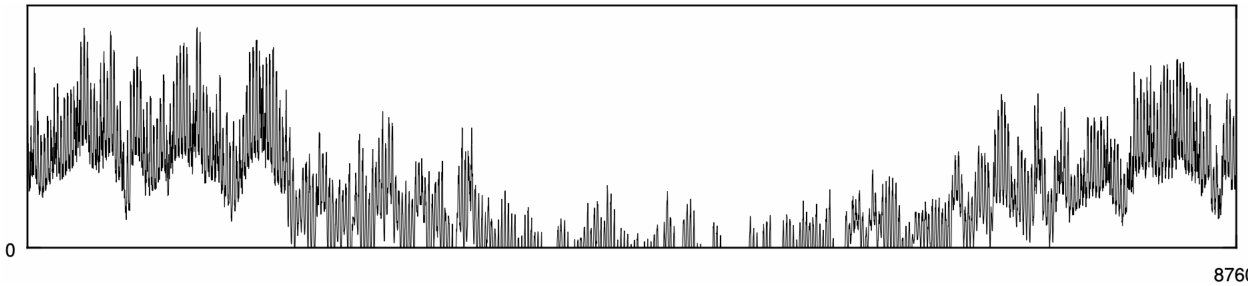

Figure 1.3: Space heating time series over the 8760 hours of the year. The demand for space heating is bigger during the winter on the left and right than during the summer in the middle as the weather is warmer during the summer. This figure comes from the documentation of EnergyScope TD [10].

Finally, is EnergyScope TD suitable for modelling a sustainable energy system in Belgium ? To transit towards a sustainable energy system, renewable energy will likely be used. In Belgium, the hydraulic power potential is low ($\sim$ 0.115 GW) but better potentials are foreseen for solar panels and wind turbines [6]. Table 1.1 presents the renewable potential in Belgium according to the PhD thesis of G. Limpens [6]. However, these renewable energies are intermittent. In order to deal with this intermittency, storage must be used [11]. As an example, during a sunny day, electricity is produced by PV panels in the middle of the day. A part of this electricity could be used for the electricity demand and the excess could be stored to be used during the evening when solar energy is not available anymore.

In order to model the operation of renewable energy coupled with storage, an hourly resolution is therefore needed. Consequently, the EnergyScope TD model is suitable for Belgium because it has this hourly resolution.

Furthermore, an hourly resolution increases the computational cost. Despite this, the EnergyScope TD model has a low computational time ($\sim$ 1 min) which makes it convenient to analyse how a sustainable energy system can operate using renewable energy and storage.

Table 1.1: Renewable potential in Belgium. The data comes from the PhD thesis of G. Limpens [6].

Technology	Potential in Belgium [GW]
Photovoltaic (PV) panel	59.2[a]
Onshore wind turbine	10
Offshore wind turbine	3.5
Hydro river	0.115
Geothermal	0
Thermal solar panel	71.4[a]

[a]This potential is obtained by assuming that 250km^2 of well-oriented and available roof exist today [6]. Those 250km^2 must be shared between PV panels and thermal solar panels. Therefore, a constrain links the capacity of PV panels and thermal solar panels in order to respect the available land area of 250km^2 assuming that the power density of PV panels and thermal solar panels are respectively 0.2367 and 0.2857 GW/km^2 [6].

1.2 EnergyScope Pathway

The EnergyScope TD model, presented above, optimises an energy system over a year. Nevertheless, when optimising only one year, the transition from the current energy system to a sustainable energy system is forgotten. This transition is actually as important as the final target since taking into account the transition cost could change the energy system at the end of the transition. Indeed, It is possible that the optimisation of the transition and the optimisation of the year 2050 do not give the same energy system for 2050.

It is also important to model the transition in order to know what is the optimal pathway towards a sustainable energy system. Is it cheaper to integrate renewable energies early or to wait until the end of the transition ? When must the technologies using fossil fuels be decommissioned ? What changes in the energy system must be realised and when ? All those questions can be answered with energy transition modelling but not necessarily with one-year energy system modelling. In section 2.1, it will be illustrated that an energy system transition modelling is needed to model the transition realistically.

Consequently, a pathway version of EnergyScope TD, named EnergyScope Pathway has been developed by Gauthier Limpens [6]. This pathway version will be explained in this section but the detailed model formulation can be found in G. Limpens PhD thesis [6]. This master thesis also offers some upgrades for this model to add realism. Those upgrades will be thoroughly explained to complement the EnergyScope Pathway description in G. Limpens' PhD thesis [6].

1.2.1 EnergyScope Pathway formulation

The methodology of the EnergyScope Pathway is illustrated in Figure 1.4. The methodology consists of applying the EnergyScope TD formulation for representative years, spaced 5 years apart, until 2050. The energy system during each representative year must respect the EnergyScope TD constraints. The representative years are linked together with the *Phases*. Additional constraints are set for those phases (e.g. the decommissioning of a technology that reaches its lifetime).

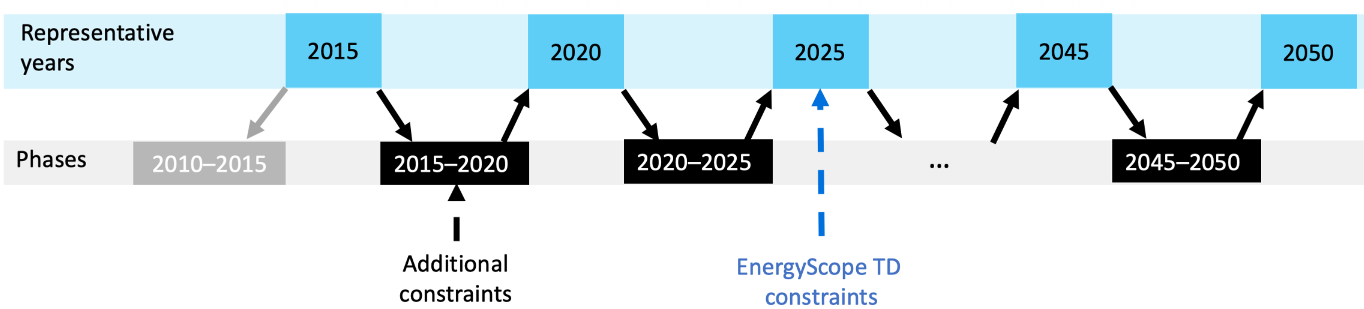

Figure 1.4: Illustration of the EnergyScope Pathway methodology. The EnergyScope TD methodology is applied for each representative years. Additional constraints are set for the phases in between representative years to realistically model the transition. This illustration comes from the PhD thesis of G. Limpens [6].

The **input parameters** of the EnergyScope Pathway are the inputs parameters of EnergyScope TD but with an additional dimension : the years. The EnergyScope Pathway parameters are forecast from today t 2050 of the EnergyScope TD parameters. As an example, in the EnergyScope TD model the end-use demands (EUDs) over a year must be given as inputs, whereas, in the EnergyScope Pathway, the EUDs during every representative year must be given as inputs.

In Chapter 4 and Appendix C of its PhD thesis, G. Limpens details the input parameters used for the case study of the Belgium transition. Those data are based on forecasts found in the literature, such as the forecast made by the European Commission for example [12]. As an example, the forecast of the end-use demands is shown in Figure 1.5. The greenhouse gas (GHG) emissions limit is also given as a parameter for each representative year to force the system to transit towards a sustainable energy system (i.e. a near-zero GHG emissions system).

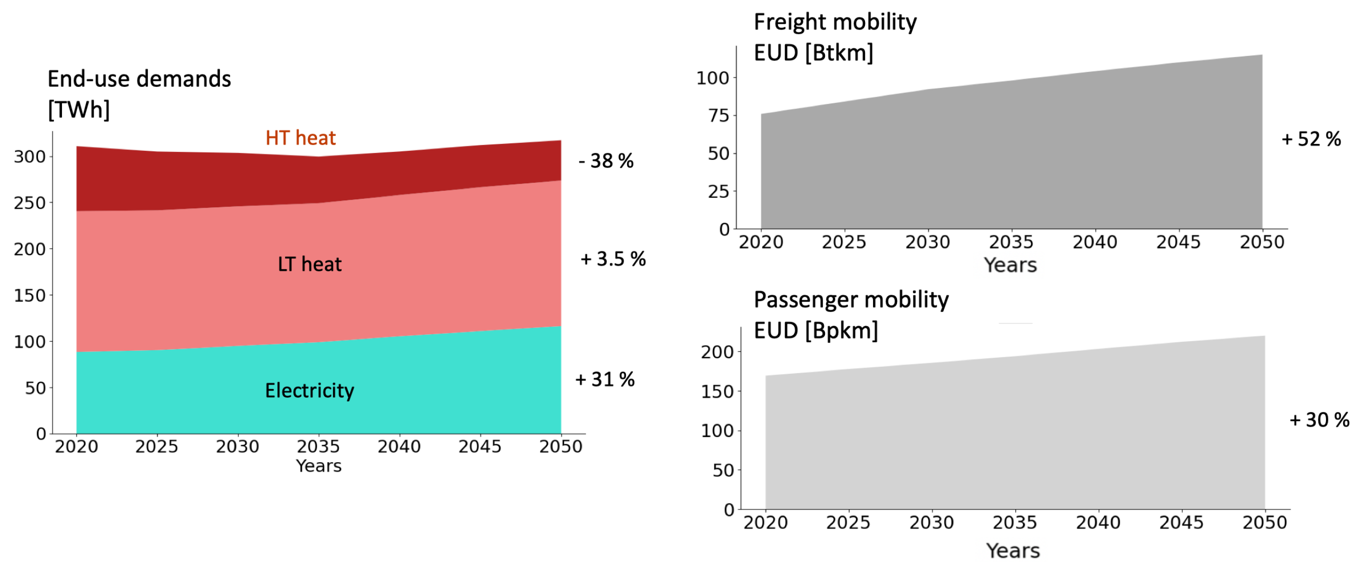

Figure 1.5: Forecast of the end-use demands (EUDs) during the transition which is an input parameter of the EnergyScope Pathway model. The percentage change between 2020 and 2050 is written for all EUDs. These data come from the PhD thesis of Gauthier Limpens [6]. Abbreviations : high temperature (HT), low temperature (LT), end-use demand (EUD), billions ton-kilometer (Btkm), billions passenger-kilometer (Bpkm).

Furthermore, a perfect foresight assumption is necessary for the formulation of the EnergyScope Pathway. Perfect foresight means that the future is assumed perfectly known (i.e. with no uncertainty). In the model formulation, it means that the input parameters (the forecast of the resources cost, the forecast of the technologies cost, etc) are given and perfectly known. This assumption allows decreasing the computational cost of the model. It is nevertheless a strong assumption. This is why an uncertainty quantification and a robust optimisation will be performed in this master thesis to take into account the uncertain aspect of the input parameters.

The **decision variables** of the EnergyScope Pathway are the installed capacity of technologies (F) and the hourly system operation (F_t) (same as EnergyScope TD) for every representative year. The technologies installed capacity are linked between the representative years through the phases with the following constraint:

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

$$\forall p \in PHASE, y_{stop} \in Y\_STOP(p), y_{start} \in Y\_START(p), i \in TECH \tag{1.1}$$

where $y_{stop}(p)$ and $y_{start}(p)$ are respectively the stopping year and the starting year of a phase p. As an example, $y_{stop}(2020\_2025) = 2025$ and $y_{start}(2020\_2025) = 2020$. $PHASE$ is the set constituted of the different phases except for the 2010_2015 phase and $TECH$ is the set constituted of the different technologies implemented in EnergyScope Pathway. This constraint means that, for a technology i, the available capacity at the end of a phase ($F(y_{stop})$) is equal to the capacity available at the beginning of the phase ($F(y_{start})$) plus the new capacity installed during this phase (F_{new}) minus the capacity that has reached its lifetime (F_{old}) minus the prematurely decommissioned capacity (F_{decom}). In other words, a technology installed during a phase will be available for future years until it is decommissioned. A technology can be decommissioned any time as long as it is done before it reaches its lifetime. An example is illustrated in Figure 1.6.

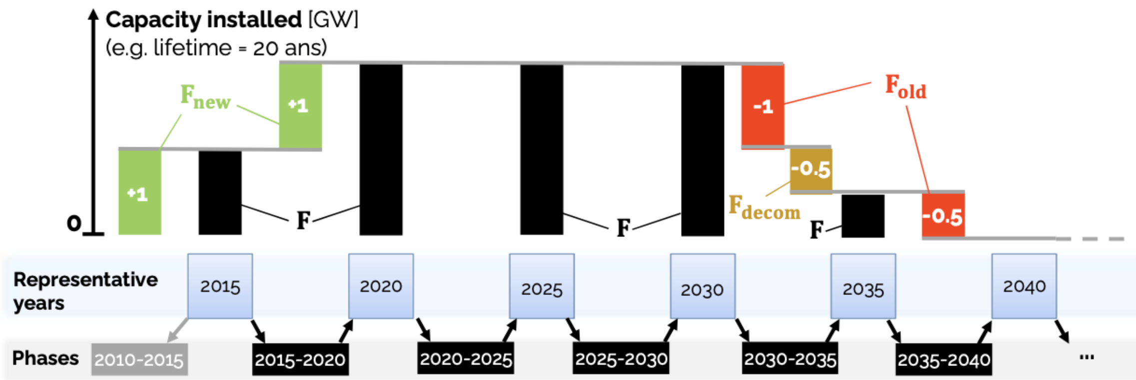

Figure 1.6: Illustrative example of technologies installation and decommissioning in the EnergyScope Pathway. This example follows the installed capacity of a technology with a 20 years lifetime during the energy transition. 1 GW is already installed before the transition (F_{new}). Between 2015 and 2020, 1 more GW is installed (F_{new}). Therefore, 2 GW of this technology is operational in 2020 (F). Those 2 GW remains operational until 2030. Between 2030 and 2035, the 1 GW installed in 2010-2015 has reached its lifetime and is consequently decommissioned (F_{old}) while 0.5 GW installed in 2015-2020 is prematurely decommissioned (F_{decom}). Therefore, only 0.5 GW is available in 2035. Between 2035 and 2040, the last 0.5 GW has reached its lifetime and is consequently decommissioned (F_{old}). This illustration comes from the PhD thesis of Gauthier Limpens (2021) [6].

The **objective function** (i.e. the value to minimise) is the total transition cost which is the sum of the total capital expenditure (CAPEX) and the total operational expenditure (OPEX) of the transition:

$$\min \quad C_{tot,trans} = C_{tot,capex} + C_{tot,opex} \tag{1.2}$$

The total OPEX of the transition is:

$$C_{tot,opex} = C_{opex}(2015) + \sum_{p \in PHASE} \underbrace{t_{phase} \cdot (C_{opex}(y_{start}(p)) + C_{opex}(y_{stop}(p)))/2 * \tau_{phase}(p)}_{\text{opex of a phase } p} \tag{1.3}$$

with $C_{opex}(y)$ the OPEX of a year y, t_{phase} the number of years in a phase (5) and $\tau_{phase}(p)$ the annualisation factor. The yearly OPEX C_{opex} and the annualisation factor τ are calculated as follows:

$$C_{opex}(y) = \sum_{tech \in TECH} C_{maint}(y, tech) + \sum_{res \in RESOURCES} C_{op}(y, res) \tag{1.4}$$

$$\tau_{phase}(p) = \frac{1}{(1 + i_{rate})^{diff\_2015\_year(p)}} \tag{1.5}$$

with C_{maint} [M€] the operating and maintenance cost of the technologies, C_{op} [M€] the operating cost of the resources, i_{rate} the real discount rate and $diff\_2015\_year(p)$ the difference in years between the phase p and 2015 (as an example $diff\_2015\_year(2030\_2035) = 2032.5 - 2015 = 17.5$).

The total CAPEX of the transition is:

$$C_{tot,capex} = \sum_{tech \in TECH} C_{inv}(2015, tech) + \sum_{p \in PHASE} C_{inv,phase}(p) \tag{1.6}$$

with C_{inv} [M€] the technologies investment cost during a year and $C_{inv,phase}$ [M€] the technologies investment cost during a phase:

$$C_{inv,phase}(p) = \sum_{tech \in TECH} F_{new}(p, tech) \cdot \tau_{phase}(p) \cdot \frac{c_{inv}(y_{start}, tech) + c_{inv}(y_{stop}, tech)}{2} \tag{1.7}$$

where F_{new} [GW] is the new installed capacity of technologies during the phase p and c_{inv} [M€/GW] is the investment cost of technologies per GW installed.

Some additional informations are necessary to comprehend the results analysed in chapter 2.

Firstly, a constraint forces the endogenous non-renewable wastes of a country to be entirely consumed during every representative year. The reason is that this master thesis is about the transition towards a sustainable energy system. The energy system of a country is more sustainable if it consumes the country's waste to produce energy rather than exporting it. Consequently, this constraint prevents the studied country from exporting its waste.

Secondly, some sectors are constrained in their change over time to avoid unrealistic changes. The change in a sector is calculated on the energy production and not on the installed capacity. The mobility and the low temperature (LT) heat sector are constrained in their changes over time to take into account human behaviour. Indeed, it would be unrealistic to replace all of today's boilers with electric heat pumps in 5 years, but it is assumed to be realistic in 20 years. Therefore, between two representative years, the change in the means of energy production in those sectors must be equal to or below 25%. It means that it must take at least 20 years to fully change how the end-use energy is produced. As an example, let's say that wood boilers and gas boilers each produce 50% of the LT heat demand and they must be substituted by heat pumps as fast as possible. After one phase, heat pumps can only produce 25% of the total LT heat by replacing only gas boilers or only wood boilers or a little of both.

Thirdly, the shares inside the mobility sector are constrained for some technologies to avoid unrealistic system during the representative years. For example, it would be unrealistic that the entire freight demand is supplied by boats, or that the public train supplies the entire passenger mobility demand. Table 1.2 contains the share limitations applied in the EnergyScope Pathway based on the data used in the PhD thesis of Gauthier Limpens [6].

Fourthly, some technologies were removed such as carbon capture and storage technologies and decentralised daily low temperature storage technologies except the storage linked to the decentralised electric heat pumps. Those technologies were removed to decrease the computational time of the EnergyScope Pathway from more than 10 hours to less than an hour. The choice of these technologies was made with Gauthier Limpens, the developer of EnergyScope Pathway, because they were deemed as the less important storage technologies.

Fifthly, the CO_2 emissions related to synthetic fuels and biofuels are neglected and the CO_2 emissions related to the imported electricity decrease from 431 to 0 [kCO_2-eq./MWh$_{\text{fuel}}$] between 2020 and 2050 as the neighbouring countries are assumed to make their energy transition at the same time as Belgium [6]. These assumptions will be discussed at the end of this master thesis.

Sixthly, the CO_2 emissions limit for each representative years only applies to the emissions related to the resources use. The CO_2 emissions related to the technologies construction is not taken into account because, otherwise, the problem of the Belgium energy transition is infeasible (i.e. EnergyScope Pathway does not find any solution that respects the CO_2 emissions limits). This master thesis will therefore focus on the Belgium energy transition towards an energy system that is carbon neutral when only the CO_2 emissions related to the consumption of resources are accounted for in the carbon footprint. This will be discussed at the end of this master thesis.

Table 1.2: Share limitations to realistically model the energy transition. The share is defined as the energy produced by a technology or a category of technology divided by the end-use demand of the corresponding sector.

	min share [%]	**max share** [%]
Public mobility	19.9[a]	50[b]
Public train[c]	0	50[b]
Tram & Trolley[c]	0	30[b]
Train freight	10[a]	25[b]
Boat freight	15[a]	30[b]
DHN	2[a]	37[b]

[a]It corresponds to the share of 2015, see Appendix A.
[b]From the PhD thesis of Gauthier Limpens (2021) [6].
[c]This share is over the public mobility.

1.2.2 Modifications in the EnergyScope Pathway

As said in the previous section, the EnergyScope Pathway used in this master thesis is slightly modified from the EnergyScope Pathway developed by Gauthier Limpens in his PhD thesis [6]. The following modifications were made to add realism to the energy transition :

1. The 2020 energy system is fixed to represent the Belgium energy system of 2020, while only the 2015 energy system was fixed in the PhD thesis of G. Limpens [6].

2. The installation of photovoltaic panels and wind turbines is limited during a phase.

3. The residual value of technologies still operational at the end of the transition is taken into account in the total transition cost.

Those changes are described in this section to complement the description of the EnergyScope Pathway in the PhD thesis of Gauthier Limpens [6].

The 2020 energy system is fixed

In order to model a realistic energy transition for Belgium, the transition should start from the current Belgium energy system. In the EnergyScope Pathway developed by Gauthier Limpens [6], the transition starts from 2015 where the energy system is fixed to represent the real Belgium energy system of 2015. Nevertheless, this master thesis is written in 2021. Therefore, it is pertinent to start the energy transition from 2020 and not 2015. Nevertheless, data for the year 2020 are still scarce. Consequently, the most recent data are used to approximate the Belgium energy system of 2020. The used data are available in Appendix A.

Furthermore, the 2015 energy system is still kept in the EnergyScope Pathway model. This means that the 2015 and the 2020 energy systems are fixed to look like the Belgium energy system in 2015 and 2020. The 2015 energy system is kept because it separates the technologies installed before 2015 from the ones installed in 2015-2020. The technologies installed before 2015 will therefore reach their lifetime and will be replaced before the technologies installed in 2015-2020.

Moreover, even though the 2015 and 2020 energy system are fixed, the results presented in chapter 2 will start from 2020 since this is the real starting point of the transition.

The integration of renewable energy is constrained

Renewable energy will likely be a crucial aspect of the energy transition in Belgium. To model more realistically this energy transition, a constraint limits the deployment per phase of technologies using renewable energy. This additional constraint is applied to the photovoltaic (PV) panels and the wind turbines. Thermal solar panels are not subject to this constraint since they are already subject to the constraint on the low temperature (LT) heat sector change (as explained earlier). The constraint limits the deployment of those 3 technologies to a percentage of their maximum potential per phase. This percentage is carried out by a new parameter $limit\_ren\_changes \in [0\,;\,1]$. The constraint is formulated as follows:

$$F_{new}(p, tech) \leq limit\_ren\_changes \cdot f_{max}(tech)$$

$$\forall p \in PHASE \backslash \{2015\_2020\}, tech \in (PV, wind\_onshore, wind\_offshore) \tag{1.8}$$

where f_{max} is the maximum installed capacity of a technology. In this case, f_{max} is equal to the renewable energy potential in Belgium (see previously in Table 1.1).

In the results analysed in Chapter 2, $limit\_ren\_changes$ is set to 0.25. Consequently, this constraint prevents the model to install more than 25% of the PV panels and wind turbines potential in one phase. As an example, the maximum capacity of PV panel that can be installed in one phase is 14.8 GW, so 25% of the potential of PV panel in Belgium (59.2 GW).

The salvage value is taken into account

According to Prina et al. [5], *the salvage value expresses the residual value of the technologies still in operation at the end of the last time-step considered.* According to Poncelet et al. [13], it is crucial to valorise the technologies still operational at the end of the transition to avoid penalising the capital intensive technologies towards the end of the transition. If the salvage value is not taken into account, the model could avoid installing some technologies at the end of the transition because it would be too expensive to pay their entire investment cost for only a short operation time. This must be prevented since the purpose of a pathway towards a sustainable energy system is to keep the energy system sustainable afterwards. Therefore, the salvage value must be taken into account when modelling an energy transition towards sustainability.

The salvage value of a technology still available in 2050 is the available capacity of the technology in 2050 times the investment cost of the technology (c_{inv} [M€/GW]) times the fraction of its lifetime that remains [5]. As an example, if a technology will still be operational for 25% of its lifetime after 2050, then the salvage value of that technology is 25% of its initial investment cost. In the EnergyScope Pathway formulation, the salvage value of a technology installed in a phase p that is still available in 2050 is computed as follows:

$$C_{inv,return}(tech, p) = \left(F_{new}(p, tech) - \sum_{p2 \in PHASE} F_{decom}(p2, p, tech) \right) * \left(1 - \frac{years\_done(tech, p)}{lifetime(tech)} \right)$$
$$* \, \tau_{phase}(p) * \Big(c_{inv}(y_{start}, tech) + c_{inv}(y_{stop}, tech) \Big) / 2 \tag{1.9}$$

with $years\_done(tech, p)$ the number of years that a technology built in a phase p will have been operational by 2050. The total salvage value $C_{inv,return,tot}$ is then computed as the sum of the technologies salvage value:

$$C_{inv,return,tot} = \sum_{tech \in TECH, p \in PHASE} C_{inv,return}(tech, p) \tag{1.10}$$

The total salvage value $C_{inv,return,tot}$ is then subtracted from the total transition cost. The total transition cost of equation 1.2 now becomes

$$\min \quad C_{tot,trans} = C_{tot,capex} + C_{tot,opex} - C_{inv,return,tot} \tag{1.11}$$

Furthermore, the expression of the salvage value $C_{inv,return}$ of a technology is similar to the expression of the salvage value in the *Transition pathways optimization methodology through EnergyPLAN software* of Prina et al. [5]. However, the salvage value could be expressed differently. In the rest of this section, different salvage value expressions are tested and compared in order to analyse the influence of the salvage value expression on the model output.

Firstly, in the expression of the salvage value presented above (see Eq. 1.9), the annualisation factor $\tau_{phase}(p)$ is the annualisation factor corresponding to the phase where the technology was built. With this expression, if a technology is still operational for half its lifetime after 2050, then half its investment cost is subtracted to the total transition cost. However, one could wonder if a technology that is still operational for half of its lifetime is not worth less than half of its initial investment cost. The annualisation factor itself aims to decrease the value of money with time because 1€ today is not worth the same as 1€ in 20 years. A technology in 2050 would therefore worth less than a technology today. In that case, the annualisation factor should be the annualisation factor of the last phase ($\tau_{phase}(2045\_2050)$) when the residual value of the technologies are calculated and subtracted from the total transition cost.

Secondly, in Eq. 1.9, the decommissioned technologies are not taken into account in the salvage value. It means that if a technology is decommissioned before 2050, then the salvage value of this technology will be 0. This is pertinent because a technology decommissioned before 2050 will not be operational after 2050. The issue is that the model could keep unnecessary technologies to subtract their salvage value from the total transition cost in order to decrease it. This would be done if the maintenance cost of an unused technology is cheaper than its salvage value. Therefore, one could wonder if it would not be better to take into account the decommissioned technologies in the salvage value. In that case, a technology that would have been operational after 2050 but is prematurely decommissioned before 2050, will have a salvage value.

Consequently, by changing the annualisation factor and the consideration of the decommissioned technologies, four different expressions could be used for the salvage value. Those four expressions are resumed in Table 1.3, along with a fifth case where the salvage value is not taken into account (i.e $C_{inv,return,tot} = 0$). The corresponding expression of the technologies salvage value in each case can be found below Table 1.3.

Those five cases are compared in Figure 1.7 to prove that the salvage value expression has little influence on the EnergyScope Pathway, but that taking into account the salvage value has a strong influence. In Figure 1.7, the last four cases are compared with the first case. Since the purpose of taking into account the salvage value is to ease the installation of some technologies at the end of the transition, the five cases were compared on the technologies installed capacity in 2050. Thus, Figure 1.7 represents the relative difference between the installed capacity of each technology in 2050 of the last 4 cases with the first case. The relative differences were calculated as follows:

$$\text{relative difference case i}\,(tech) = \frac{F_{case\,1}(2050, tech) - F_{case\,i}(2050, tech)}{max\big(F_{case\,1}(2050, tech), F_{case\,i}(2050, tech)\big)} \tag{1.12}$$

with F the installed capacity of a technology in a given year.

Table 1.3: Different cases for the salvage value expression. For notice, if decommissioned technologies are not taken into account then an X is written in this table and the term with F_{decom} is present in the expressions below to subtract the capacity that has been decommissioned before 2050. For the annualisation factor $\tau_{phase}(p)$, the phase p is either the phase where the technology was built (p_{built}) or the last phase of the transition (2045_2050).

Case	name in Figure 1.7	Decommissioned technologies taken into account	$\tau_{phase}(p)$
1	Without decom building phase	X	$p = p_{built}$
2	Without decom 2045-2050	X	$p = 2045\_2050$
3	With decom building phase	V	$p = p_{built}$
4	With decom 2045-2050	V	$p = 2045\_2050$
5	Without $C_{inv,return}$	/	/

$$C_{inv,return}(tech,p) = (F_{new}(p,tech) - \sum_{p2 \in PHASE} (F_{decom}(p2,p,tech)) * (1 - \frac{years\_done(tech,p)}{lifetime(tech)}) * \tau_{phase}(p) * (c_{inv}(y_{start},tech) + c_{inv}(y_{stop},tech))/2 \quad \text{(case 1)}$$

$$C_{inv,return}(tech,p) = (F_{new}(p,tech) - \sum_{p2 \in PHASE} (F_{decom}(p2,p,tech)) * (1 - \frac{years\_done(tech,p)}{lifetime(tech)}) * \tau_{phase}(2045\_2050) * (c_{inv}(y_{start},tech) + c_{inv}(y_{stop},tech))/2 \quad \text{(case 2)}$$

$$C_{inv,return}(tech,p) = F_{new}(p,tech) * (1 - \frac{years\_done(tech,p)}{lifetime(tech)}) * \tau_{phase}(p) * (c_{inv}(y_{start},tech) + c_{inv}(y_{stop},tech))/2 \quad \text{(case 3)}$$

$$C_{inv,return}(tech,p) = F_{new}(p,tech) * (1 - \frac{years\_done(tech,p)}{lifetime(tech)}) * \tau_{phase}(2045\_2050) * (c_{inv}(y_{start},tech) + c_{inv}(y_{stop},tech))/2 \quad \text{(case 4)}$$

$$C_{inv,return}(tech,p) = 0 \quad \text{(case 5)}$$

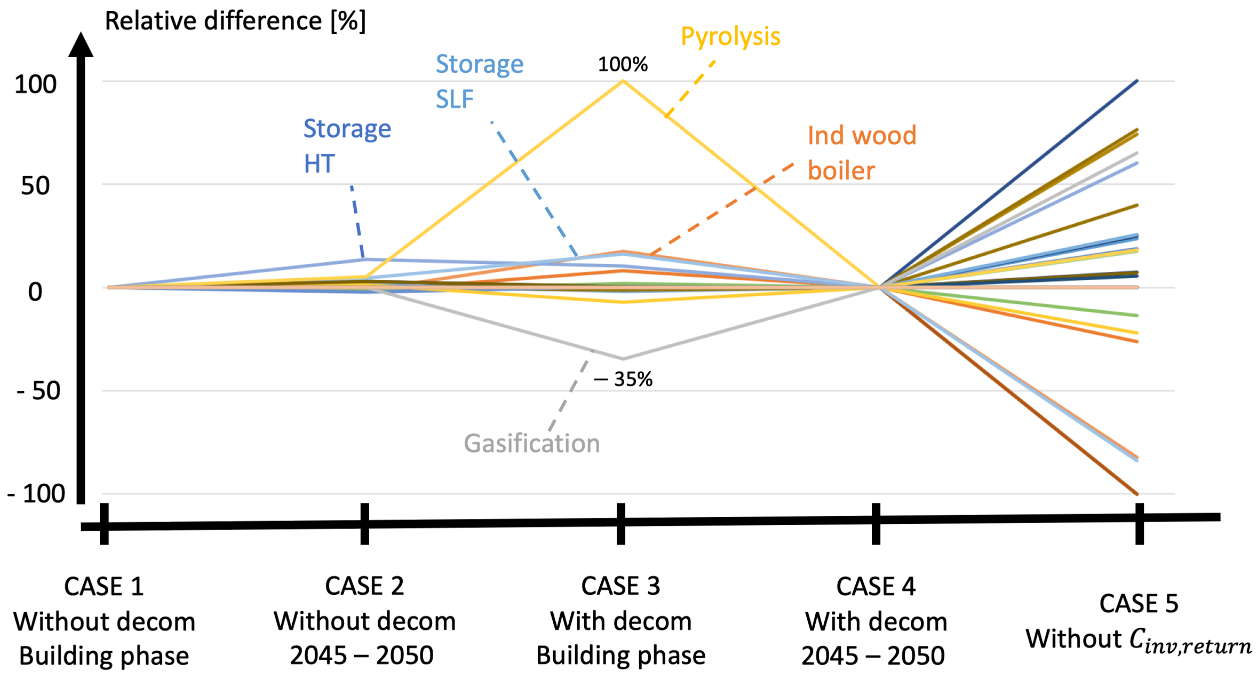

Figure 1.7: Relative difference between the first case and the other cases of Table 1.3 on the installed capacity of technologies in 2050. The relative differences are calculated with equation 1.12. In case 2, only one technology (high temperature storage) has a relative difference higher than 10% compared to case 1. In case 3, four technologies have a relative difference higher than 10%. Abbreviations : high temperature (HT), synthetic liquid fuel (SLF).

First of all, in Figure 1.7, there is a strong difference between the installed capacity of technologies at the end of the transition in a scenario where the salvage value is taken into account (case 1 to 4) and a scenario where it is not (case 5). This illustrate the importance of taking into account the salvage value of technologies.

Furthermore, the salvage value expression has little influence on the energy system of 2050. Concerning the consideration of decommissioned technologies in the salvage value, only four technologies (on the 85 technologies present in the model) have a relative difference bigger than 10% between case 1 and case 3. As a reminder, the difference between those cases is that in case 1 the decommissioned technologies are not taken into account in the salvage value while in case 3 they are. Since only 5 technologies out of the 85 present a significant difference (above 10%), the first and third case are considered relatively similar. Moreover, the two technologies with the biggest differences are pyrolysis and gasification infrastructure, which are two minor technologies with small installed capacities (1.4 and 2.5 GW). Therefore, taking or not the decommissioned technologies in the salvage value has little influence on the 2050 energy system.

Concerning the phase p considered for the annualisation factor $\tau_{phase}(p)$, case 1 and 2 are relatively similar since only one technology has a relative difference over 10% (high temperature storage with 13.7%) which illustrates that the annualisation factor also has little influence on the energy system of 2050.

In conclusion, it is crucial to take into account the salvage value of technologies in the total transition cost, otherwise the installed capacities in the 2050 energy system strongly differ. On the other hand, the expression of the salvage value has little influence on the technologies installed capacity in the 2050 energy system. Therefore, any of the expression presented above could be used. In the rest of this master thesis, the salvage value will be expressed as in the first case (Eq. 1.9) which is also the expression used in the EnergyPLAN software [5].

1.3 Simplified EnergyScope Pathway

The EnergyScope Pathway model, described above, takes around 1500 seconds to find the optimal transition that minimises the total transition cost. Nevertheless, a computationally cheaper pathway model is needed in order to perform an uncertainty quantification or a robust optimisation. Indeed, it will be explained later that the number of model evaluations required for an uncertainty quantification has an order of magnitude of 10^3. Accounting for 10^3 model evaluations and each evaluation taking 1500 seconds, it will take more than two weeks to perform an uncertainty quantification.

A simplified version of EnergyScope Pathway is described in this section and will be called *Simplified EnergyScope Pathway*. The purpose of the Simplified EnergyScope Pathway model is to be a good approximation of the EnergyScope Pathway model while being computationally cheaper. This purpose is reached since Simplified EnergyScope Pathway is 5 times faster than EnergyScope Pathway with a relative error on the optimal transition cost of less than 1%. This is demonstrated in appendix B. In the same appendix, it is also demonstrated that the transition strategy is similar between an optimised transition with EnergyScope Pathway and with Simplified EnergyScope Pathway which is also an important feature. Consequently, the Simplified EnergyScope Pathway model is a good approximation of the EnergyScope Pathway model and will be used for an uncertainty analysis in chapter 3 and a robust optimisation in chapter 4.

The main difference between the Simplified EnergyScope Pathway and the EnergyScope Pathway is that a time step of 10 years between the representative years is considered instead of 5 years, as illustrated in Figure 1.8. The Simplified EnergyScope Pathway is faster than the EnergyScope Pathway because there is twice less representative years and therefore twice less decision variables.

Some additional modifications were needed in order to create the Simplified EnergyScope Pathway:

1. The Simplified EnergyScope Pathway model must start in 2020 in order to go from 2020 to 2050 with a time step of 10 years. The 2020 energy system is fixed to represent the Belgium energy system of 2020. All the technologies present in the 2020 energy system are assumed to have been installed between 2010 and 2020.

2. The constraint on the change of the mobility and low temperature heat sector must be adapted. In EnergyScope Pathway, the change in those sectors was limited to 25% per phase. Since the phases in Simplified EnergyScope Pathway are twice longer, the change in those sectors will be limited to 50% per phase. Consequently, in both model, those sectors need at least 20 years to fully change.

3. The constraint on the renewable energy installation is adapted similarly to the previous point. The installation was limited to 25% of the renewable potential in Belgium per phase in EnergyScope Pathway. Therefore, the installation will be limited to 50% per phase in Simplified EnergyScope Pathway.

4. The phase where a technology must be decommissioned based on its building phase has also been adapted. In EnergyScope Pathway, most of the technologies have a lifetime that is a multiple of 5. It is therefore easy to manage the decommissioning of technologies with phases of 5 years. In Simplified EnergyScope Pathway, the technologies lifetime are rounded down to the nearest multiple of 10 for their decommissioning. Let's take for example a PV panel with a lifetime of 25 years. In Simplified EnergyScope Pathway, its lifetime is rounded to 20 years, meaning that a PV panel installed in 2020-2030 will be decommissioned in 2040-2050. Rounded down is prefered to rounded up to prevent technologies to better respect their lifetime. However, some technologies have a lifetime of 17 or 18 years. In that case, the lifetime is rounded up to 20 years because this configuration best approximates the total transition cost of the EnergyScope Pathway model.

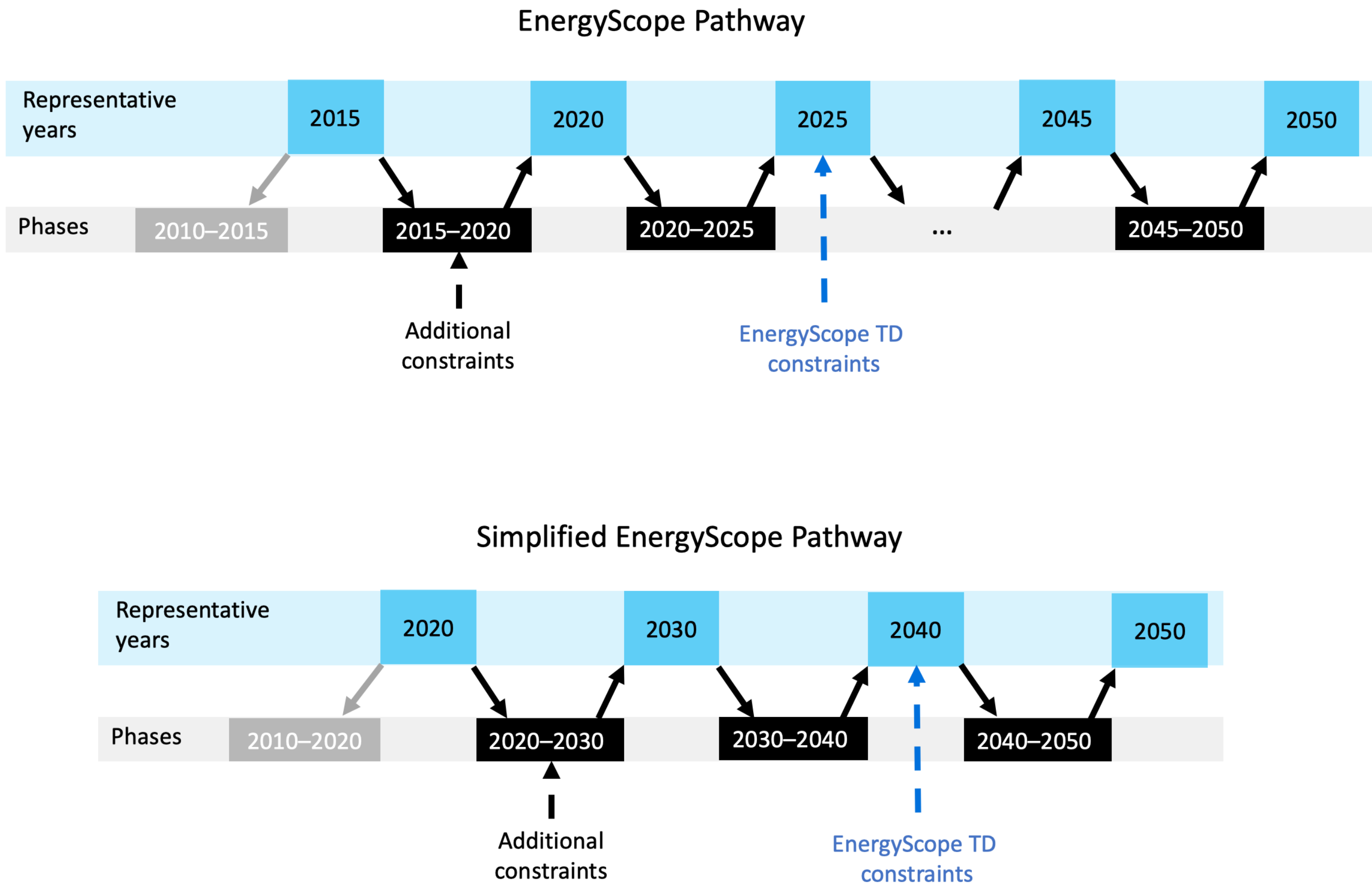

Figure 1.8: Illustration of the Simplified EnergyScope Pathway methodology compared to the one of the EnergyScope Pathway. The Simplified EnergyScope Pathway has a time step of 10 years and is therefore constituted of 4 representative years which is twice less than the EnergyScope Pathway.

Chapter 2

Results on the Belgium energy transition

This chapter presents results on the Belgium energy transition when uncertainties are not yet taken into account. Gauthier Limpens, in his PhD thesis [6], already analysed the Belgium energy transition, optimised with EnergyScope Pathway, but only for one of the four scenarios analysed in this master thesis (i.e. the basic scenario). Therefore, in this master thesis, more answers will be given on how Belgium can transit optimally towards energy sustainability depending on the transition context. Moreover, the EnergyScope Pathway was improved between the PhD thesis of G. Limpens [6] and this master thesis. Therefore, the pathway he analysed is slightly different than the pathway, in the same scenario, analysed in this master thesis (e.g. battery electric vehicles are used in the pathway analysed in this master thesis).

In section 2.1, the EnergyScope Pathway will be compared to what is called a *snapshot optimisation* in order to prove that using a one-year energy system model to model an energy transition gives an unrealistic transition compared to the EnergyScope Pathway model. Then, in section 2.2, EnergyScope Pathway will be used to model and optimise the energy transition for a *basic scenario*. The resulting energy transition will be analysed to understand what is the cost-optimal transition towards a sustainable energy system in Belgium. Afterwards, in section 2.3, three alternative scenarios with different contexts, modelled and optimised with EnergyScope Pathway, will be compared to the basic scenario. The purpose is to analyse how the energy transition may change depending on the transition context (e.g. if nuclear is phased out or not). For section 2.2 and 2.3, the contexts of the basic scenario and the 3 alternative scenarios are the following:

- **Basic scenario** : In this scenario, the phasing-out of nuclear power plants in Belgium will be modelled by allowing to have 2 GW of nuclear power plants until 2025 and then no nuclear power plants will be available. Electricity can be imported from other countries but with limited availability.

- **Nuclear scenario** : This scenario is similar to the basic scenario, except for the phasing-out of nuclear power plants. In this scenario, it is assumed that the 5.925 GW of nuclear power plants existing nowadays, in Belgium, can be extended until 2050. The purpose is to analyse the potential benefits of extending the existing nuclear power plants.

- **Zero Imported Electricity scenario** : This scenario is similar to the basic scenario, except for the availability of imported electricity. In this scenario, Belgium will not be able to import electricity from neighbouring countries during its transition towards energy sustainability.

- **Phase budget scenario** : This scenario is similar to the basic scenario, except for the investment during the phases (i.e. the 5-year periods). In this scenario, the investments to install technologies must be constant in every phase. The purpose is to help politicians to determine a fixed budget to install new technologies for the transition towards sustainability and analyse the consequence of a fixed budget in the Belgium energy transition.

2.1 Pathway optimisation vs Snapshot optimisation

In section 1.2, the EnergyScope Pathway methodology has been explained. The model optimises the total transition cost while making sure the energy system is operational every five years. In this model, the representative years are linked together. If a technology is installed in a phase, then it will be available in the future phases as long as its lifetime is not reached.

However, another way to model the energy transition could be to use a snapshot model for every representative years. As a reminder, a snapshot model represents the energy system in a target future year. With a snapshot model, the energy transition could be modelled by using a snapshot model to optimise the energy system annual cost of every representative year. It is like taking a snapshot of the energy system every five years and assemble those snapshots together to model the energy transition. Consequently, in this case, the representative years would not be linked together (see Figure 2.1).

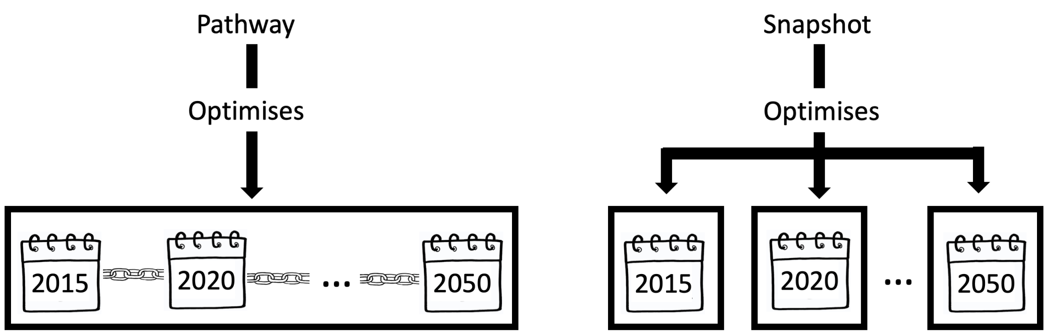

Figure 2.1: Schematic of the pathway methodology and a snapshot methodology. The pathway optimises the total transition cost and the energy system of the representative years are linked together. The snapshot optimises separately the energy system annual cost of the representative years and those energy systems are not linked together in time.

The advantage of a snapshot optimisation is that it takes less time to model the energy transition than the pathway ($\sim$ 5 times faster). Nevertheless, the disadvantage of the snapshot optimisation is that there is no link between the energy systems in time, which impacts the reality of the modelled transition. Indeed, the evolution of the installed capacity of technologies is smoother with the pathway than with the snapshot optimisation, as shown in Figure 2.2 for the CCGTs.

In the snapshot optimisation, between 2030 and 2045, the CCGT capacity decreases, then increases and finally decreases again. In reality, it would mean that some CCGTs are decommissioned, then 5 years later some CCGTs are installed to finally be decommissioned after 5 years, which is not realistic.

In the pathway optimisation, realised with EnergyScope Pathway, the CCGT capacity is steady over time. It is not economically efficient to install some CCGTs to decommission them later. But this conclusion can only be drawn by the model if it has a perception of time, and if the energy systems are linked together in time. This is why the pathway optimisation results in a more realistic energy transition than a snapshot optimisation.

Moreover, in EnergyScope Pathway, the change of some energy sectors during a phase is limited (as explained in section 1.2) but it can not be in a snapshot optimisation since the representative years are not linked together. Consequently, the transition strategy changes between the pathway and the snapshot optimisation, as illustrated in Figure 2.3. In the snapshot optimisation, thermal heat pumps (thHP) are installed as an

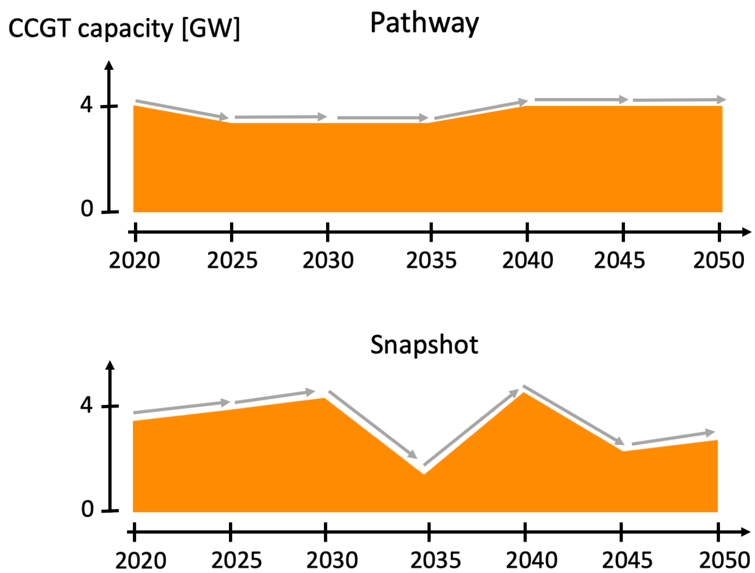

Figure 2.2: Capacity of combined cycle gas turbine (CCGT) operational during the transition with a pathway optimisation and a snapshot optimisation. The CCGT capacity is steady with a pathway optimisation but sharp with a snapshot optimisation.

intermediate solution, to substitute the fossil fuels boilers, before being substituted by electric heat pumps (eHP). However, in the pathway optimisation, no thHP is installed. The model prefers to install the eHPs as soon as possible because it must take at least 20 years to fully change the low temperature heat sector. Therefore, the used technologies sometimes differ between the snapshot and the pathway optimisation, which means that the snapshot optimisation does not accurately approximate the energy transition strategy of a pathway optimisation.

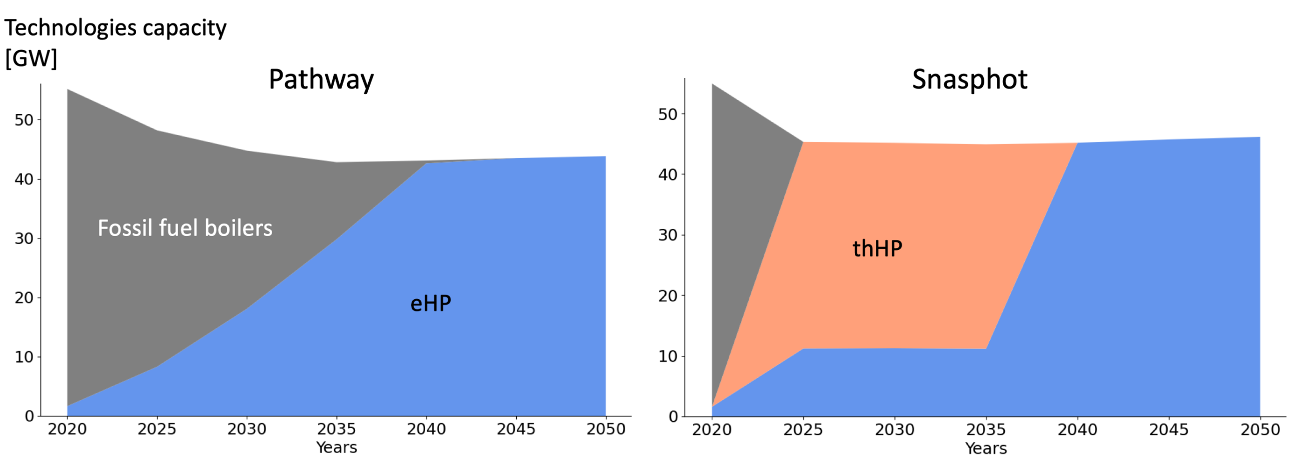

Figure 2.3: Capacity of low temperature (LT) heat technologies during the transition with a pathway and a snapshot optimisation. Thermal heat pumps (thHP) are used in the snapshot optimisation but not in the pathway optimisation. The energy transition strategy differs.

To conclude, a snapshot optimisation lacks realism and the transition strategy is different from a pathway optimisation. Therefore, a snapshot optimisation is not a good approximation of the EnergyScope Pathway optimisation. This reinforces the need of using a pathway model, with a time perception, that optimises the total transition cost, to realistically model an energy transition.

2.2 Basic scenario

The basic scenario is a scenario related to the current events in Belgium. A nuclear power phase-out is planned for 2025. In his PhD thesis, Gauthier Limpens made a hypothesis that only Tihange 3 and Doel 4 (2 GW) will be working in 2025 while the other plants will be phased out between 2020 and 2025. This hypothesis will be kept in this scenario. Therefore, in this basic scenario, 5.925 GW of nuclear power were available in 2020, 2 GW will be available in 2025 and then no nuclear power plants will be available.

Belgium is usually a net-importer of electricity. In fact, according to the press release from Elia [14], Belgium has been an electricity importing country from 2009 until 2019. In this scenario, Belgium is able to import a limited amount of electricity from neighbouring countries. This amount increases from 25625 GWh in 2025 to 32440 GWh in 2050 (see Table C.2 in G. Limpens PhD thesis [6]).

As explained in section 1.2, the energy system of 2020 is constrained to represent the real Belgium energy system of 2020. The year 2020 is the starting point of the transition. The characteristics of the 2020 Belgium energy system are detailed in Appendix A.

In this section, the Belgium energy transition, optimised with EnergyScope Pathway for this basic scenario, is analysed through two sub-sections. First, in section 2.2.1, the four most important aspects of the optimal Belgium energy transition, in this scenario, will be analysed. Those four aspects represent the four keys to transit optimally towards a sustainable energy system in Belgium. Then, in section 2.2.2, the transition of the energy sectors and the resources used during this transition will be analysed in more details.

2.2.1 Four keys for the Belgium energy transition

This transition scenario is characterised by four major changes in the energy system, or four keys to transit, in the cheapest way, towards a sustainable energy system in Belgium. The four keys are the following:

1. During the transition, current technologies are substituted by more efficient technologies.

2. Fossil fuels are substituted by imported electricity, renewable energy and synthetic fuels.

3. The system is electrified to fully use the electricity produced by photovoltaic panels and wind turbines

4. Storage technologies are used to manage the intermittency of renewable energy.

The first key for the Belgium energy transition is the **use of more efficient technologies**. During the transition, current technologies are replaced by more efficient technologies. For example, heat pumps and public transport (e.g. buses, trains and tramways) substitute boilers and cars, respectively, for the demand of low temperature heat and passenger mobility. Consequently, the used resources decrease from 559 to 309 TWh between 2020 and 2050, even though the end-use demands are foreseen to increase in almost every sectors. This means that consumers will demand more energy but fewer resources will be needed to supply this increasing demand thanks to the higher efficiency of new technologies.

More efficient technologies are used because the greenhouse gas (GHG) emissions decrease if fewer resources are consumed. Consequently, it is easier to respect the GHG emissions limits.

The second key for the Belgium energy transition is the **substitution of fossil fuels**. The Belgium energy system in 2020 is based on fossil fuels with only 7% of renewable energy (with the data in Appendix A). During the transition, fossil fuels are progressively substituted in order to decrease the GHG emitted by the energy system, as shown in Figure 2.4. Liquide fuel oil (LFO) and gasoline are the first fossil fuels to be replaced between 2020 and 2030. Then, diesel and coal are replaced between 2030 and 2040. Natural gas (NG) is the last fossil fuel to be replaced. It is the most preferable fossil fuel to use during the energy transition because it is cheaper and emits less CO_2 per GWh than any other fossil fuels.

In 2050, 78% of the emissions are due to the combustion of non-renewable waste, 14% are due to the use of wet biomass and 8% are due to the use of wood. As a reminder, all the available non-renewable waste is forced to be consumed in order to prevent it from being exported.

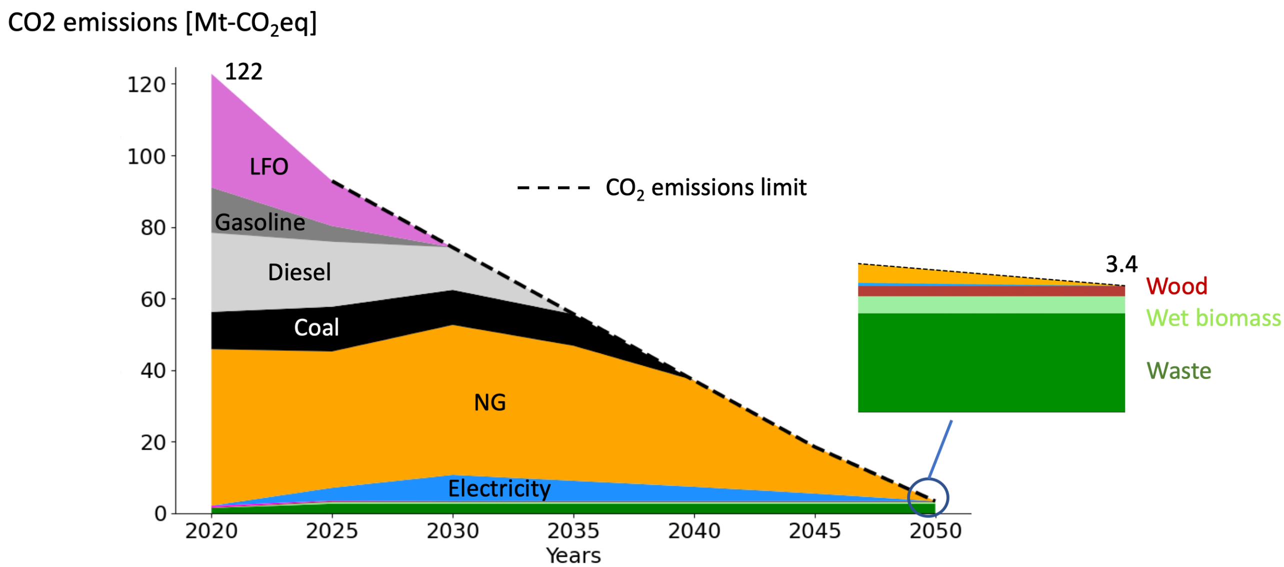

Figure 2.4: Fossil fuels are substituted during the energy transition as the CO_2 emissions limit decreases to reach a sustainable energy system in 2050. Abbreviations : liquid fuel oil (LFO), natural gas (NG).

Figure 2.5 shows what substitute fossil fuels during the energy transition. First, fossil fuels are partially substituted by renewable energies and imported electricity between 2020 and 2040. Renewable energies are massively deployed during this period and electricity importation is increased. In 2040, the entire photovoltaic and wind turbine potential in Belgium is used (59.175 GW of PV panels and 13.5 GW of wind turbines), all the available electricity from neighbouring countries is imported (29.18 TWh) and all the available biomass is used (23.4 TWh of woody biomass and 38.9 TWh of wet biomass). The resources used in 2040 are 50% renewable, 41% fossil and 9% imported electricity.

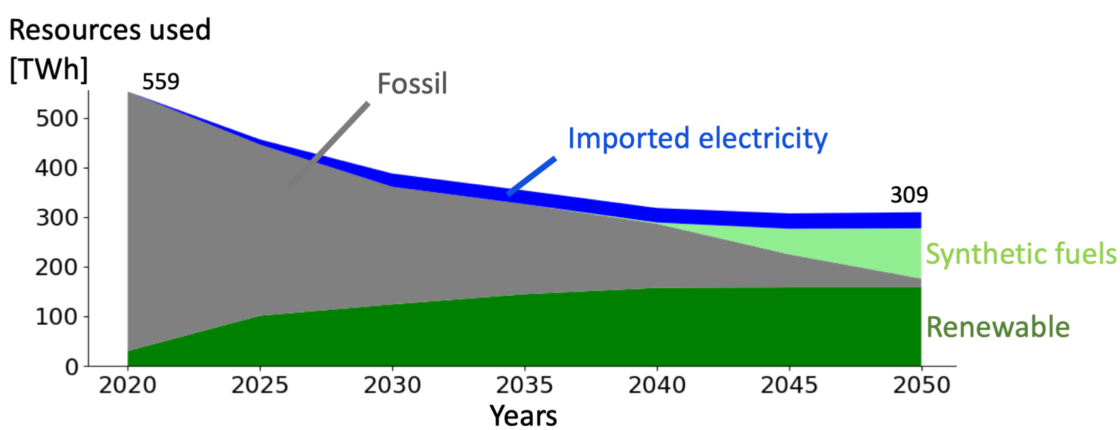

Figure 2.5: Fossil fuels are replaced by imported electricity, renewable energy and synthetic fuels.

Then, between 2040 and 2050, synthetic fuels are used to substitute the rest of fossil fuels except the non-renewable waste. The used synthetic fuels are hydrogen (H_2) and synthetic natural gas (SNG). In 2050, the used resources are 51% renewable, 6% fossil (waste), 32% synthetic fuels and 11% imported electricity.

The third key for the Belgium energy transition is the **electrification of the energy system**. The electrification of a sector is the percentage of end-use energy produced in the sector by technologies consuming electricity.

In 2020, 97% of the produced electricity is used to meet the electricity demand. During the transition, the heat and mobility sectors are progressively electrified for 3 main reasons :

- The heat and mobility sectors use the electricity produced by photovoltaic (PV) panels and wind turbines to substitute the fossil fuels used in those sectors.

- It improves the efficiency of the energy system as the technologies, used to electrify the system, are more efficient than the technologies used nowadays. As an example, the train and tramway are more efficient than a private car, and an electric heat pump is more efficient than a fossil fuel boiler.

- The peak of electricity produced by PV panels during the middle of a sunny day is more easily absorbed if more technologies consume electricity. This will be illustrated later.

The energy system electrification is shown in Figure 2.6. Between 2020 and 2040, the maximum potential of PV panels (59.175 GW) and of wind turbines (10 GW onshore and 3.5 GW offshore) is installed. To meet the demand when renewable energies are not producing electricity, electricity is imported, 3.2 GW out of the 3.9 GW of CCGTs available in 2020 are kept during the entire transition and industrial gas cogeneration of heat and power (CHP) are installed (0.9 GW in 2020-2025 and 1.8 additional GW in 2035-2040). With the massive installation of PV and wind turbines, the production of electricity increases between 2020 and 2040 at a higher rate than the electricity demand (see Fig. 2.6). The excess of electricity is consequently used in the heat and mobility sectors. In 2050, 26% of the electricity is used to produce low temperature (LT) heat, 2% is used to produce high temperature (HT) heat, 3% is used for passengers mobility and 1% is used for freight mobility.

Figure 2.7 shows the increase of the sectors electrification. The most electrified sector is the LT heat sector which is 100% electrified from 2040. This sector is electrified by installing electric heat pumps (eHP) to substitute the fossil fuel boilers. From 2040, the LT heat demand is entirely supplied by eHPs.

The passenger mobility sector is progressively electrified between 2020 and 2040 until 70% of this sector is electrified (see Fig. 2.7). Private mobility is electrified by using battery electric vehicles (BEV) while public mobility is electrified by using the train and the tramway up to their limit (limit previously presented in Table 1.2). Then, between 2040 and 2050, BEVs are replaced by hydrogen cars which decreases the electrification of this sector (see Fig. 2.7).

The freight mobility sector is only electrified at 25% through trains used up to their limit (limit previously presented in Table 1.2).

Finally, the high temperature (HT) heat sector is the less electrified sector with only 8.5% of electrification in 2050 (see Fig. 2.7). The reason is that waste is forced to be consumed and the cheapest way is by using industrial waste boilers to produce HT heat. Furthermore, as explained earlier, industrial gas CHP is used to produce HT heat but also electricity which will be used to electrify the other sectors. The HT heat sector will only be 8.5% electrified by using 5 GW of industrial electric heaters.

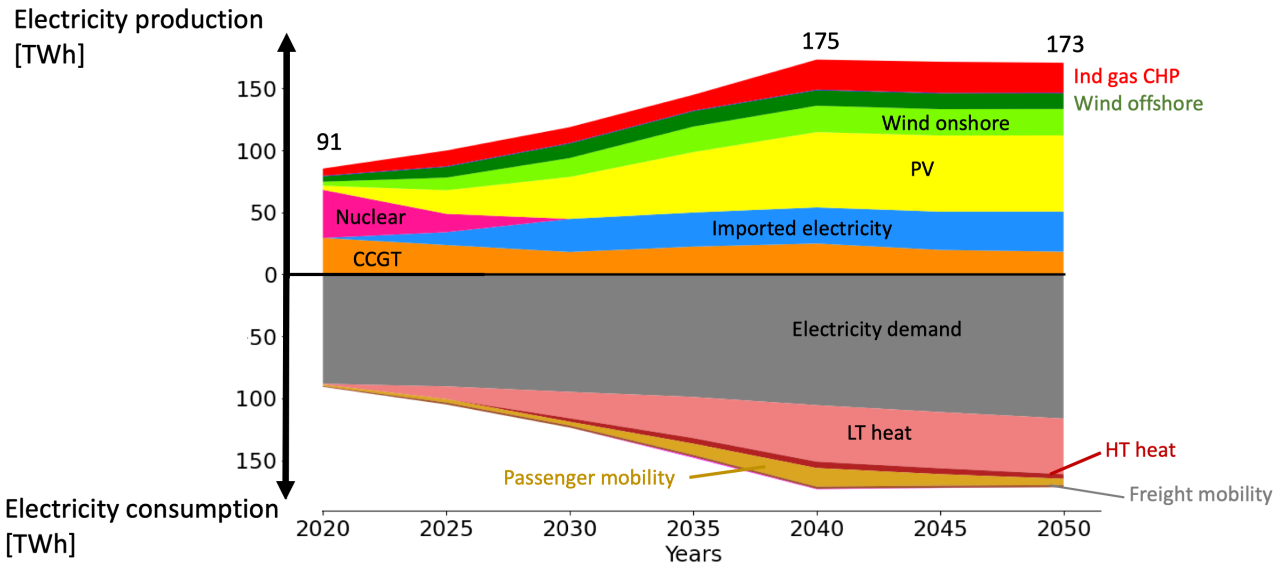

Figure 2.6: Balance of the electricity sector during the energy transition. The production of electricity increases during the transition as photovoltaic (PV) panels and wind turbines are massively installed. The excess of electricity will be used in other energy sectors to electrify those sectors. Abbreviations : Industrial gas cogeneration of heat and power (Ind gas CHP), photovoltaic (PV), combined cycle gas turbine (CCGT), low temperature (LT), high temperature (HT).

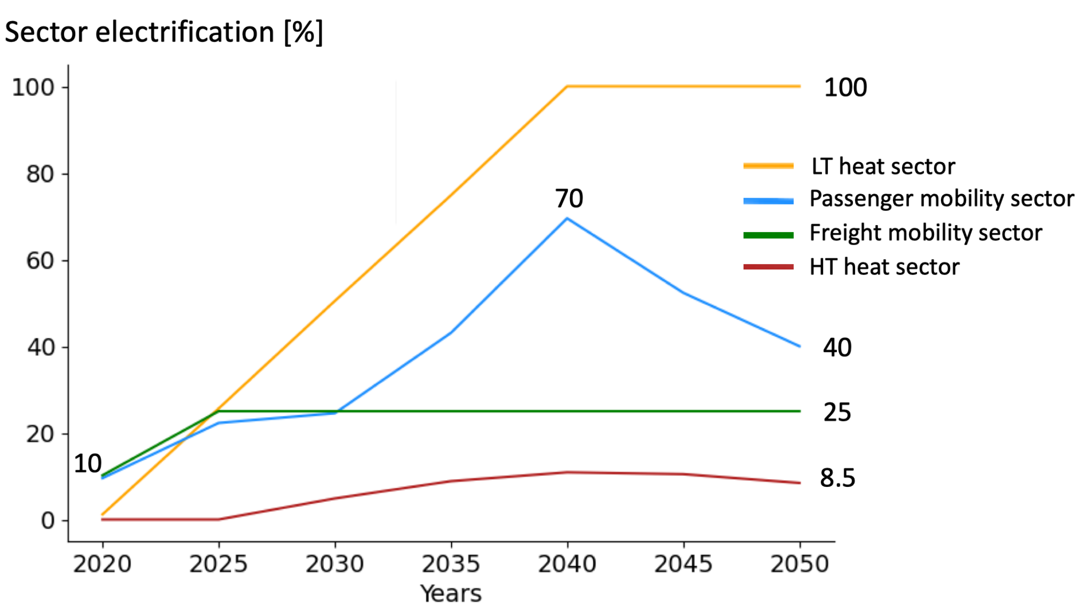

Figure 2.7: The different energy sectors are electrified during the energy transition. The electrification of a sector is the percentage of end-use energy produced in this sector by technologies consuming electricity. Abbreviations : low temperature (LT), high temperature (HT).

The fourth and last key of the Belgium energy transition is the **use of storage technologies** to manage the intermittency of renewable energies. As previously explained, PV panels and wind turbines are massively installed from 2020 to achieve their potential limit by 2040. The issue with renewable energy is its intermittency. PV panels and wind turbines only produce electricity when the sun is shining or the wind is blowing, which is not controllable.

In this transition scenario, the intermittency of solar energy is more problematic than the intermittency of wind energy. Generally, wind energy is available during days where the LT heat demand is high (cloudy/cold days), whereas solar energy is more available during days where the LT heat demand is low (sunny/warm days). Moreover, the potential of PV panels in Belgium (59.175 GW) is almost 6 times higher than the potential of wind turbines in Belgium (13.5 GW). As a consequence, the electricity peak produced by PV panels during sunny days exceeds the energy demands (electricity demand, electricity for eHP, ...) while the electricity produced by wind turbines never exceed the energy demands, as illustrated in Figure 2.8.

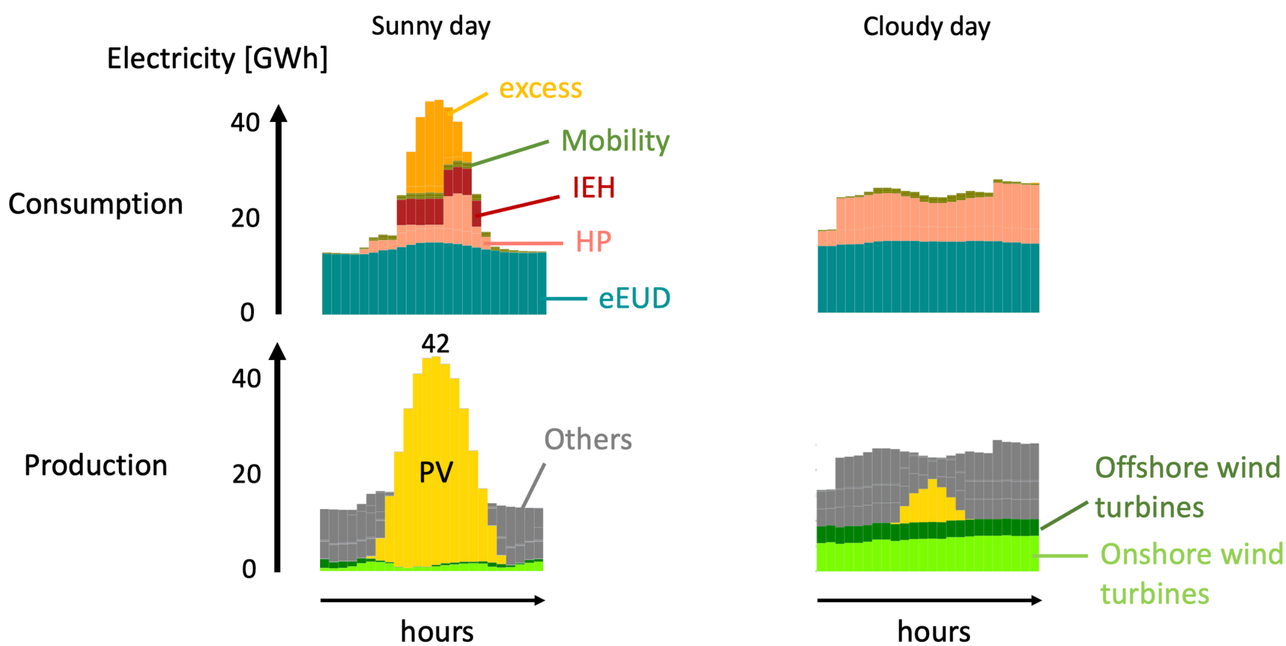

Figure 2.8: Electricity balance during a typical sunny and cloudy day in 2050. In the middle of a sunny day, photovoltaic (PV) panels produce too much electricity compared to the electricity demand and the demands of other energy sectors, whereas, in the morning and the night, the demand can not be meet with renewable energy. During a cloudy day, not enough electricity is produced by renewable energy to meet the energy demands. To meet the demands when renewable energy can not, other technologies are used (e.g. CCGT, CHP, imported electricity). Abbreviations : electric heat pump (eHP), industrial electric heater (IEH), electricity end-use demand (eEUD).

Consequently, storage technologies are used to manage the intermittency and the electricity peak of PV panels (up to 42 GWh in 2050). First, let's understand how this is managed. The operation of the electricity and LT heat sector during a typical sunny day in 2050 is represented in Figure 2.9. In 2050, lithium batteries, decentralised daily thermal storage and DHN seasonal thermal storage are used. Lithium batteries are used to store the excess of electricity from the solar energy's peak. This electricity can then be used during the early morning or the night when solar energy is not available. Additionally, LT heat will be produced by electric heat pumps (eHP) during the peak of electricity. However, the LT heat demand is low at that time. This heat will therefore be stored to be used in the early morning and the night.

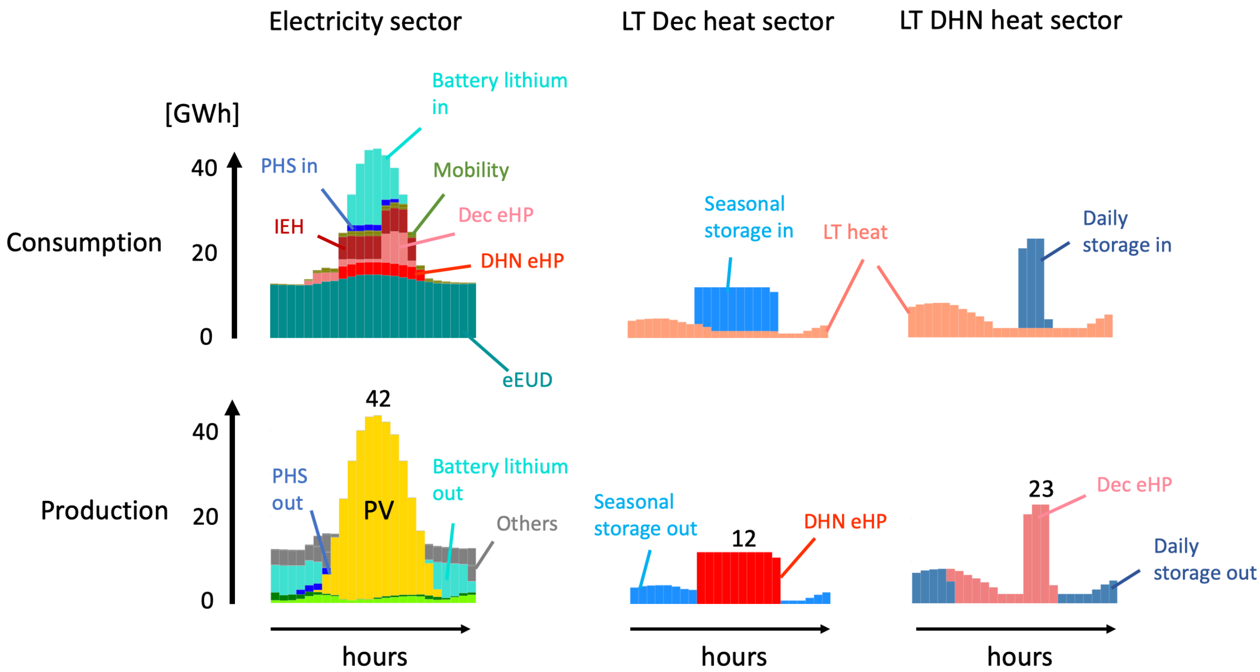

Figure 2.9: Energy balance during a typical sunny and warm day in 2050. The peak of electricity from PV panels is partially absorbed by lithium batteries and by electric heat pumps (eHP). The LT heat produced by eHPs is not needed since the demand is small when the sun shines. This produced heat will consequently be stored in thermal storage (TS) and will be used during the night or early morning when the LT heat demand is higher. Abbreviations : low temperature (LT), high temperature (HT), district heating network (DHN), decentralised (Dec), electricity end-use demand (eEUD), heat end-use demand (hEUD).

Furthermore, the different daily storage technologies are not installed at the same moment in the transition, as shown in Figure 2.10. The first storage that is installed is the pumped hydropower storage (PHS). From 2025 to 2050, PHS will be used up to its maximum potential (6.5 GW).

However, since PV panels are massively installed between 2020 and 2040, more storage is needed. From 2025 to 2040, decentralised daily thermal storage (TS) and battery electric vehicles (BEV) are deployed to manage this increase of PV panels (see Figure 2.10). The installation of decentralised daily TS is in parallel with the electrification of the LT heat sector from 2020 to 2040 explained earlier. Electricity from solar panels can be used to produce heat and store it to be used later when needed, as explained above in Figure 2.9. Moreover, BEV batteries play a similar role to lithium batteries in 2050 thanks to the vehicle-to-grid (V2G) concept. The V2G concept is based on the idea that the battery of electric vehicles can exchange electricity with the grid. During a sunny day, the BEV can store the excess of electricity and supply the grid afterwards when it is needed, just like lithium batteries do in 2050.

Then, from 2040, the total capacity of PV panels remains constant (59.175 GW). From 2040 to 2050, BEVs are replaced by hydrogen cars. Therefore, the electricity from PV panels used in BEVs can be used elsewhere to further reduce CO_2 emissions. As a consequence, lithium batteries substitute the battery of electric vehicles between 2040 and 2050.

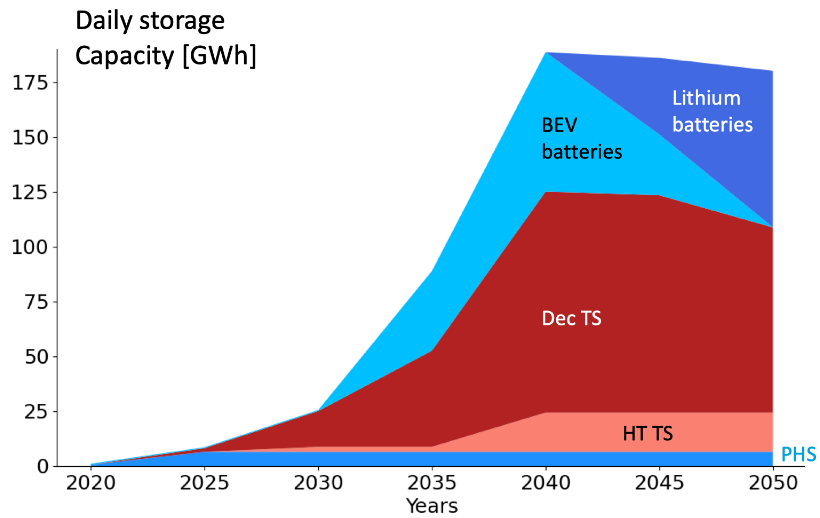

Figure 2.10: Daily storage technologies are progressively installed during the transition to manage the installation of PV panels. Abbreviations : battery electric vehicle (BEV), thermal storage (TS), decentralised (dec), high temperature (HT), pumped hydropower storage (PHS).

The previous paragraphs explained how and when the daily storage technologies are implemented into the system. Furthermore, between 2020 and 2040, district heating network (DHN) seasonal storage is also installed up to 1.865 TWh of storage capacity in 2040. This storage is used similarly to the decentralised daily thermal storage as explained earlier (see Figure 2.9). Moreover, the DHN seasonal storage is also used seasonally by storing low temperature (LT) heat during the summer to use this heat during the winter when the demand is higher and PV panels produce less electricity. This is illustrated in Figure 2.11 for the year 2040.

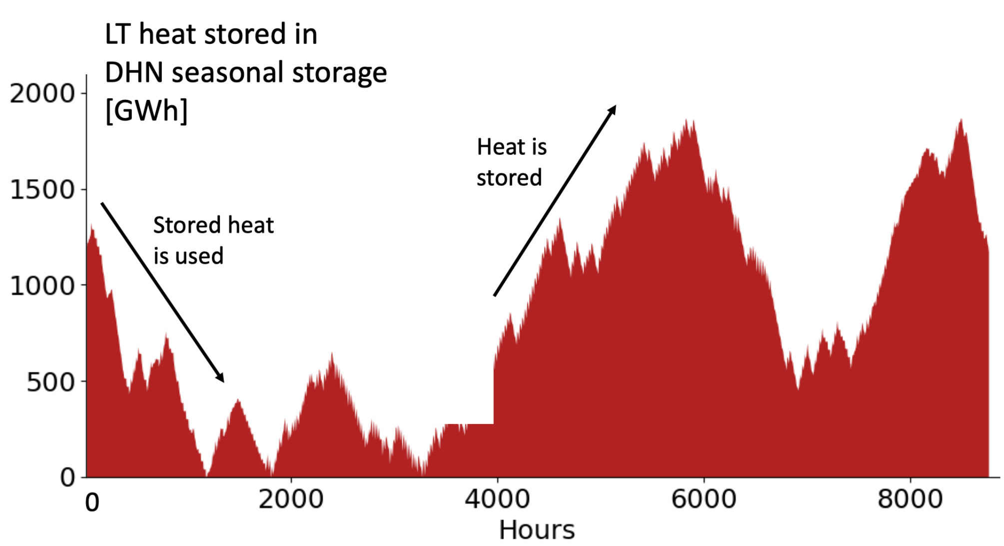

Figure 2.11: Low temperature (LT) heat stored in DHN seasonal storage over the year 2040. LT heat is stored during the spring and summer on the right to be used during fall and winter on the left when solar energy is less available and the LT heat demand is higher.

2.2.2 Sectors and resources analysis

In the previous section, the four keys for the Belgium energy transition were explained : the use of more efficient technologies, the substitution of fossil fuels, the electrification of the system and the use of storage technologies. In this section, a more detailed analysis of the sectors and the used resources will be performed.

Figure 2.12 shows the evolution of the low temperature (LT) heat sector during the transition. From 2020 to 2040, the current fossil fuel boilers are progressively substituted, starting with liquid fuel oil (LFO) boilers, by 30.5 GW of decentralised electric heat pumps (eHP) and 12 GW of district heating network (DHN) eHP. Those electric heat pumps are more efficient and electrify completely this sector in 2040. Furthermore, the DHN is used up to its limit of 37% because it is more efficient and cheaper than decentralised technologies.

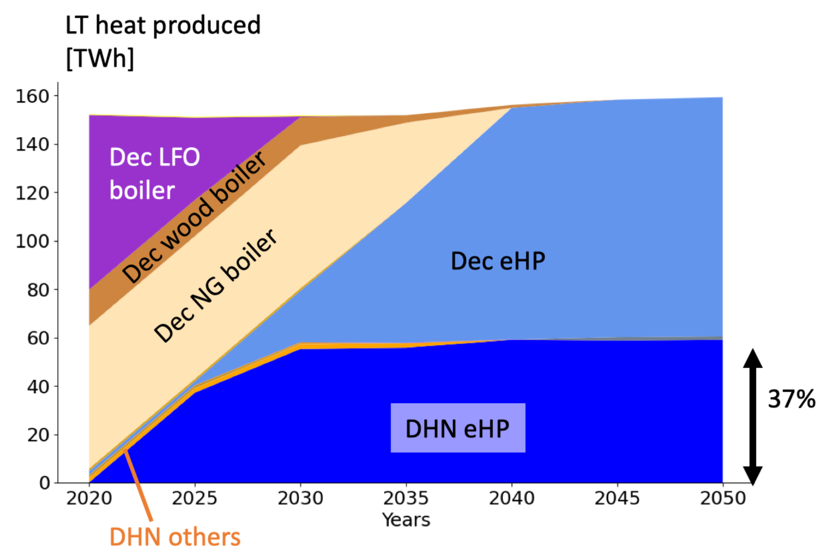

Figure 2.12: Low temperature (LT) heat production during the transition. Fossil fuel boilers are substituted by electric heat pumps between 2020 and 2040. Abbreviations : liquid fuel oil (LFO), natural gas (NG), electric heat pump (eHP), decentralised (Dec), district heating network (DHN).

For HT heat sector, the HT heat production during the energy transition is represented in Figure 2.13. The boilers used nowadays are replaced by 3.2 GW of waste boilers, to use all the available waste, and by 3.5 GW of industrial gas cogeneration of heat and power (CHP), using natural gas (NG) in the beginning of the transition and then synthetic natural gas (SNG) at the end of the transition. Additionally, industrial electric heaters (IEH) are also installed and are used during sunny days to absorb a part of the electricity produced by PV panels. The maximum installed capacity of industrial electric heater is 8 GW in 2040.

For the passenger mobility, the technologies production are shown in Figure 2.14. Public mobility is increased as fast as possible to produce 50% of the demand from 2025, which is its limit (limit previously presented in Table 1.2). This shows the higher efficiency of public mobility compared to private mobility. Moreover, public mobility is electrified through the tramway and the train that are used up to their limit from 2025 and from 2040 respectively. In private mobility, hydrogen cars are the best option to substitute fossil fuel cars in the long-term. However, battery electric vehicles (BEV) are used as an intermediate solution, from 2030 to 2050, to decarbonise private mobility at a lower cost than using only hydrogen cars since hydrogen is expensive.

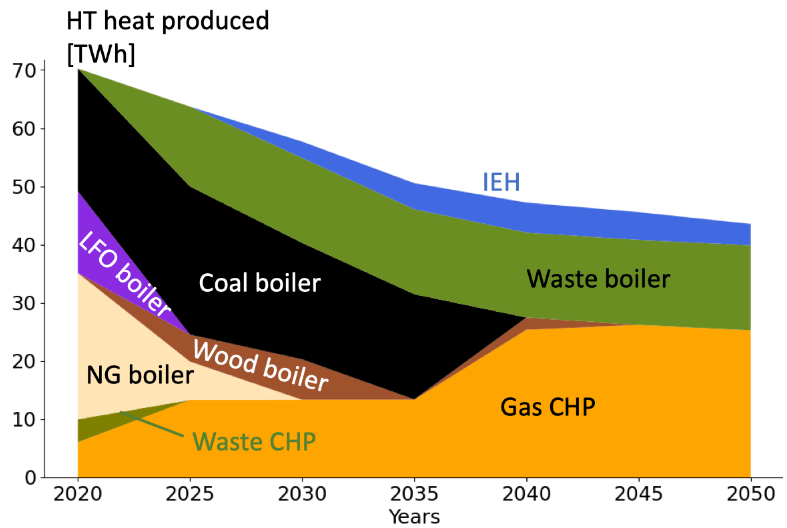

Figure 2.13: High temperature (HT) heat production during the transition. Abbreviations : liquid fuel oil (LFO), natural gas (NG), cogeneration of heat and power (CHP), industrial electric heater (IEH).

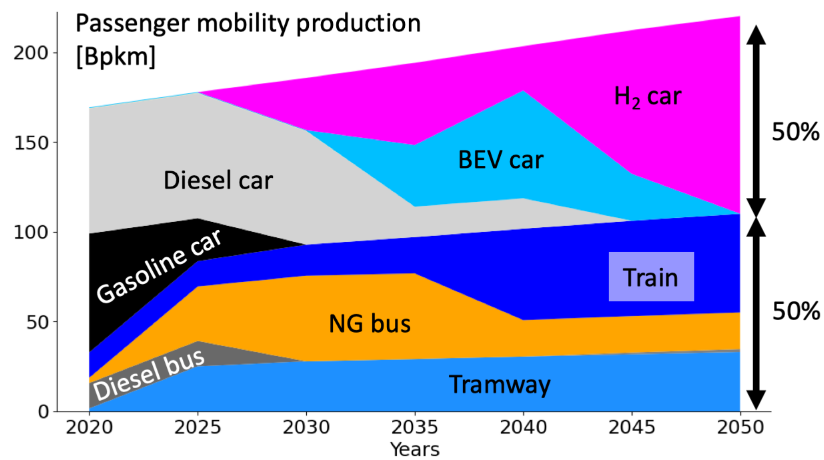

Figure 2.14: Passenger mobility production during the transition. Public transports increases in order to supply 50% of the demand from 2025. Fossil fuel cars are substituted by hydrogen cars and BEVs. Finally, in 2050, the only cars are hydrogen cars. Abbreviations : billions of passenger-km (Bpkm), natural gas (NG), battery electric vehicle (BEV), hydrogen (H_2).

For freight mobility, the technologies used during the transition are shown in Figure 2.15. Diesel trucks are progressively substituted by trains, NG boats and new trucks. The boat and the train are used to their limit (30% and 25%) from 2025 until the end of the transition. H_2 trucks are deployed from 2025 and supply 45% of the freight demand by 2045. Nevertheless, some NG trucks are used as an intermediate solution between 2025 and 2045 because they emit less CO_2 emissions than diesel trucks and NG is cheaper than H_2.

The deployment of the infrastructure technologies is presented in Figure 2.16. 2.2 GW of hydrolysis infrastructure are installed between 2020 and 2025 and are used during the rest of the transition to produce 16.5 TWh/year of natural gas (NG) from 38.9 TWh/year of wet biomass. Between 2025 and 2045, steam methane reforming (SMR) is used to produce H_2 from NG because it is cheaper than importing H_2 and hydrogen transports are used from 2025. However, from 2045, H_2 is imported because SMR emits too much CO_2. Between 2030 and 2035, 1.7 GW of pyrolysis infrastructure are installed and are used during the rest

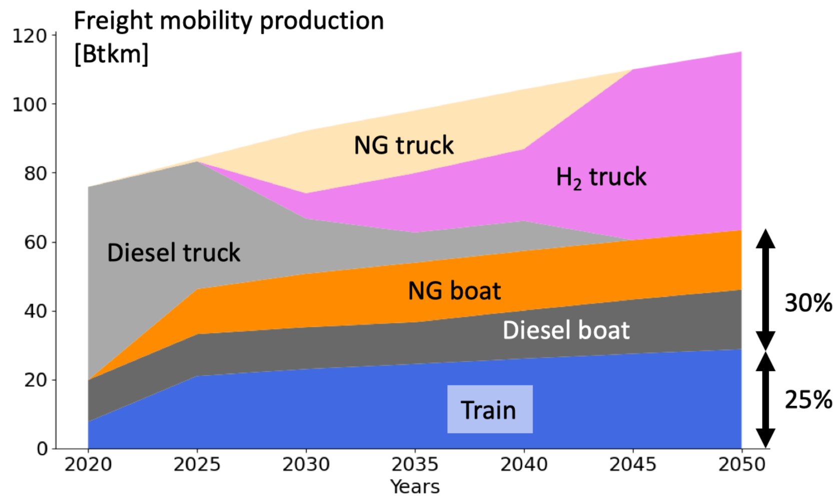

Figure 2.15: Freight mobility production means during the transition. Abbreviations : billions of ton-km (Btkm), natural gas (NG), hydrogen (H_2).

of the transition to convert woody biomass into synthetic liquid fuel (SLF). This SLF will be used by freight boats. Finally, between 2040 and 2045, 2.2 GW of gasification infrastructure is installed to convert woody biomass to natural gas (NG) during the rest of the transition. By the end of the transition, all the available woody and wet biomass (23.4 and 38.9 TWh [6]) are converted into 32.8 TWh/year of NG and 2 TWh/year of SLF by gasification, pyrolysis or hydrolysis.

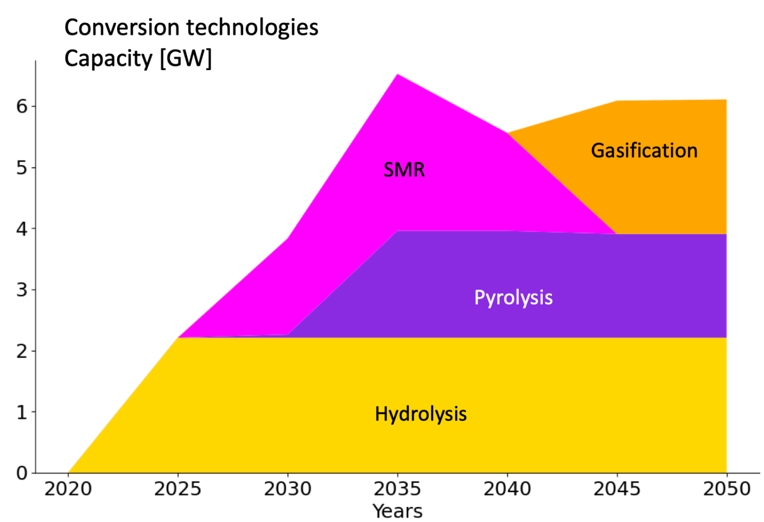

Figure 2.16: Evolution of the infrastructure technologies capacity during the transition. Abbreviations : steam methane reforming (SMR), synthetic natural gas (SNG).

The resources used during the transition are shown in Fig. 2.17. Analysing the used resources is a good conclusion of the Belgium energy transition towards sustainability. The used resources decrease during the transition because more efficient technologies are used. Furthermore, fossil fuels are replaced by renewable energy (solar, wind, biomass), imported electricity and synthetic fuels (H_2, SNG). Natural gas (NG) has a major role to play in the Belgium transition as it is cheap and emits less CO_2 than the other fossil fuels. Solar and wind energy are used to produce green electricity and will drive the energy system electrification. Biomass is used in infrastructure technologies to convert it into NG and SLF. Hydrogen (H_2) is used in fuel cell technologies in the mobility sector. Waste is entirely consumed in waste boilers to produce HT heat. Finally, SNG is used in boats and buses but also in CCGTs and industrial gas CHP to produce electricity when solar and wind energy are not available and storage technologies are empty.

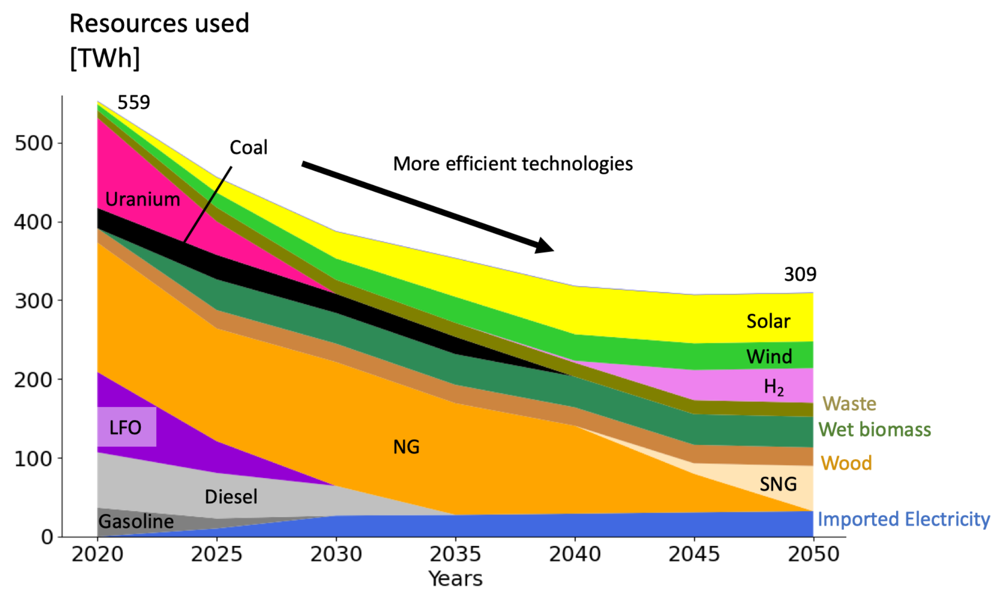

Figure 2.17: Resources used during the transition. Fewer resources are needed throughout the transition as more efficient technologies are used. Moreover, fossil fuels are substituted by renewable energy, imported electricity and synthetic fuels. Abbreviations : liquid fuel oil (LFO), natural gas (NG), hydrogen (H2), synthetic natural gas (SNG).

2.3 Alternative scenarios

In this section, the three alternative scenarios, described at the beginning of this chapter and further described in their corresponding sub-section, will be optimised by EnergyScope Pathway and compared to the Belgium energy transition of the basic case that has just been analysed.

2.3.1 Nuclear scenario

The nuclear scenario is a scenario where there is no phasing-out of the nuclear power plants in Belgium. It is assumed that the 5.925 GW of nuclear power plants operational today will be operational until 2050. The purpose of this nuclear scenario analysis is to understand how the nuclear power plants could help the Belgium energy transition. The resulting transition for this scenario with the EnergyScope Pathway model will be compared to the basic scenario transition analysed in the previous section. As a reminder, in the basic scenario, there were no nuclear power plants after 2025 because of the nuclear phase-out.

First of all, in the nuclear scenario transition optimised with EnergyScope Pathway, the 5.925 GW of nuclear power plants in Belgium are used during the entire transition to produce 44 TWh of electricity every year, as shown in Figure 2.18. The electricity produced by nuclear power plants substitutes the electricity imported from 2025 to 2040 in the basic scenario transition, it progressively substitutes CCGTs during the transition, and it substitutes a part of the industrial gas CHP that was installed during the basic scenario transition (0.9 GW are substituted in 2020-2035 and 1.3 GW in 2035-2050).

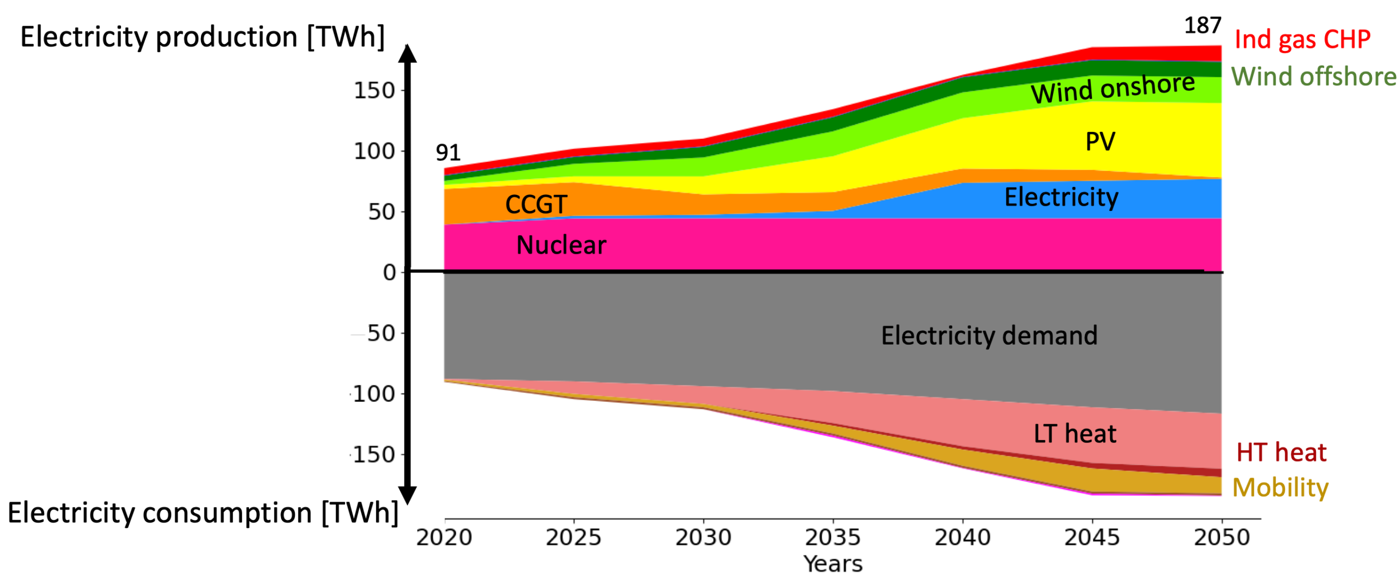

Figure 2.18: Balance of the electricity sector during the transition when 5.925 GW of nuclear power plants is operational in Belgium. Nuclear power is used as much as possible (44 TWh of electricity/year). This Figure can be compared to Figure 2.6 which was the electricity produced and consumed in the basic scenario transition. Abbreviations : Industrial gas cogeneration of heat and power (Ind gas CHP), combined cycle gas turbine (CCGT), low temperature (LT), high temperature (HT).

Nuclear power is used firstly because it is financially interesting. In fact, nuclear power plants decrease the total transition cost by 9% compared to the basic scenario (786 B€ vs 870 B€). The first reason is that nuclear power plants replace a part of the power plants used in the basic scenario (CCGTs, industrial gas CHP) which decreases the transition CAPEX. The second reason is that, in the model, uranium has the lowest operation cost (0.0039 M€/ GWh) of all the resources. Therefore, using uranium during the transition reduces the transition OPEX.

Moreover, nuclear power is used during the transition because it emits a very low amount of CO_2 in proportion to the electricity it produces. To produce 44 TWh of electricity per year from 2020 to 2050, the nuclear power plants emit 0.43 Mt-CO_2eq/year, which is very low compared to the rest of the energy system CO_2 emissions, as shown in Figure 2.19. This represents only 13% of the CO_2 emissions in 2050. Nuclear energy is therefore compatible with a sustainable energy system in the long-term.

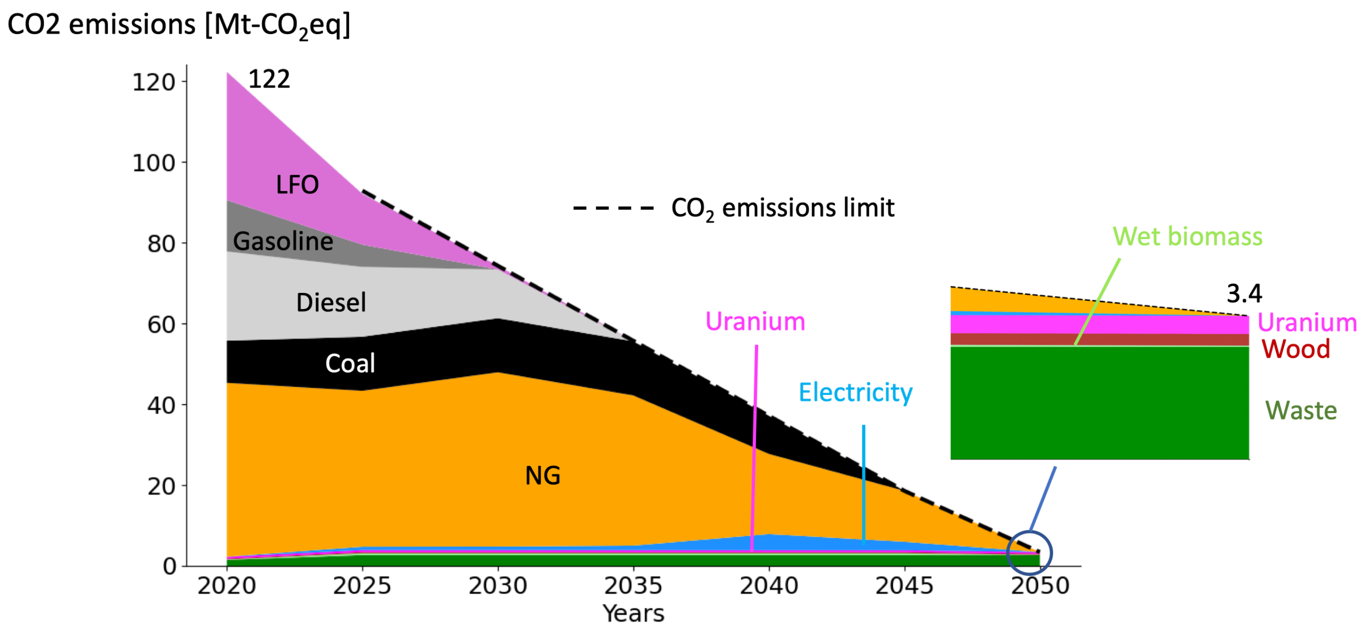

Figure 2.19: Fossil fuels are substituted during the transition to decrease the CO_2 emissions, just like in the basic scenario. Moreover, the CO_2 emissions related to uranium are minor. In 2050, 13% of the CO_2 emissions come from the use of uranium. Abbreviations : liquid fuel oil (LFO), natural gas (NG).

Furthermore, the installation of photovoltaic (PV) panels and offshore wind turbines is slower in the nuclear scenario transition than in the basic scenario transition, as shown in Figure 2.20. Indeed, since nuclear power emits few CO_2 emissions, it can replace a part of the renewable energies in the beginning of the transition. However, to respect the CO_2 emissions limit in 2050, the full potential of PV panels and wind turbines is used. It means that a sustainable energy system in 2050 can not be based only on our nuclear power. Nevertheless, nuclear power plants can slow down the deployment of renewable energy while respecting the CO_2 emissions limits.

The energy system electrification is also slower when nuclear power plants are operational, as shown in Figure 2.21. As it was explained for the basic scenario transition, the electrification of the system follows the deployment of renewable energy in order to absorb the electricity peak from PV panels and decrease the CO_2 emissions in other sectors than the electricity sector. Since PV panels and offshore wind turbines are installed more slowly in the nuclear scenario, the energy system electrification can also be slower. However, at the end of the transition, the system electrification is higher than in the basic scenario. This is due to the fact that more electricity can be produced cheaply while respecting the CO_2 emissions limit because of the nuclear power plants. The mobility sector is more electrified by substituting half of the hydrogen cars with battery electric vehicles (BEV). The high temperature (HT) heat sector is also more electrified in 2050 as 3.6 more GW of industrial electric heaters is installed compared to the basic scenario.

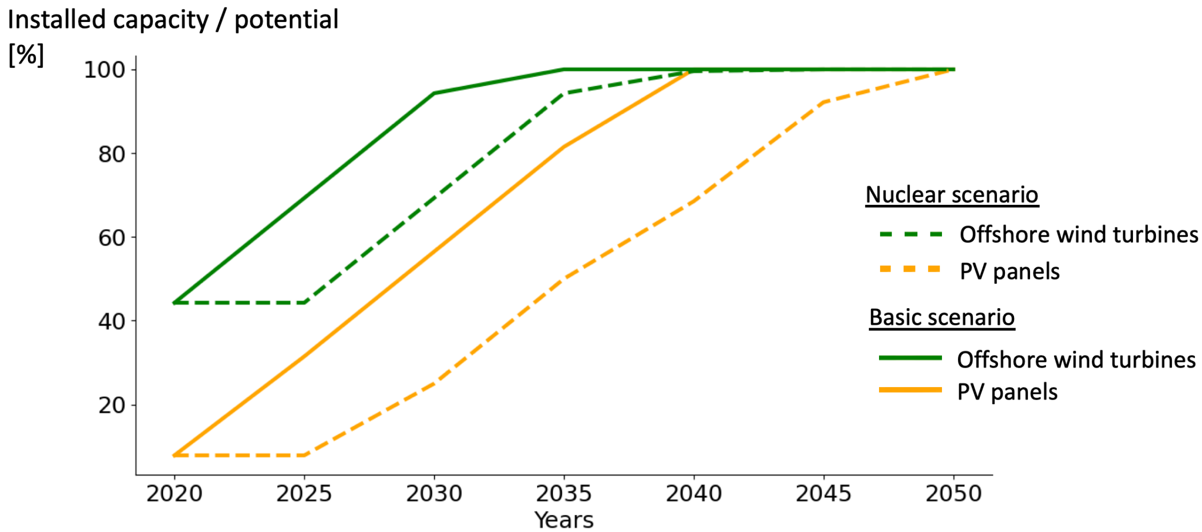

Figure 2.20: Installed capacity of offshore wind turbines and photovoltaic (PV) panels during the transition divided by their maximum potential in Belgium. The available nuclear power plants in Belgium allow photovoltaic (PV) panels and offshore wind turbines to be installed more slowly

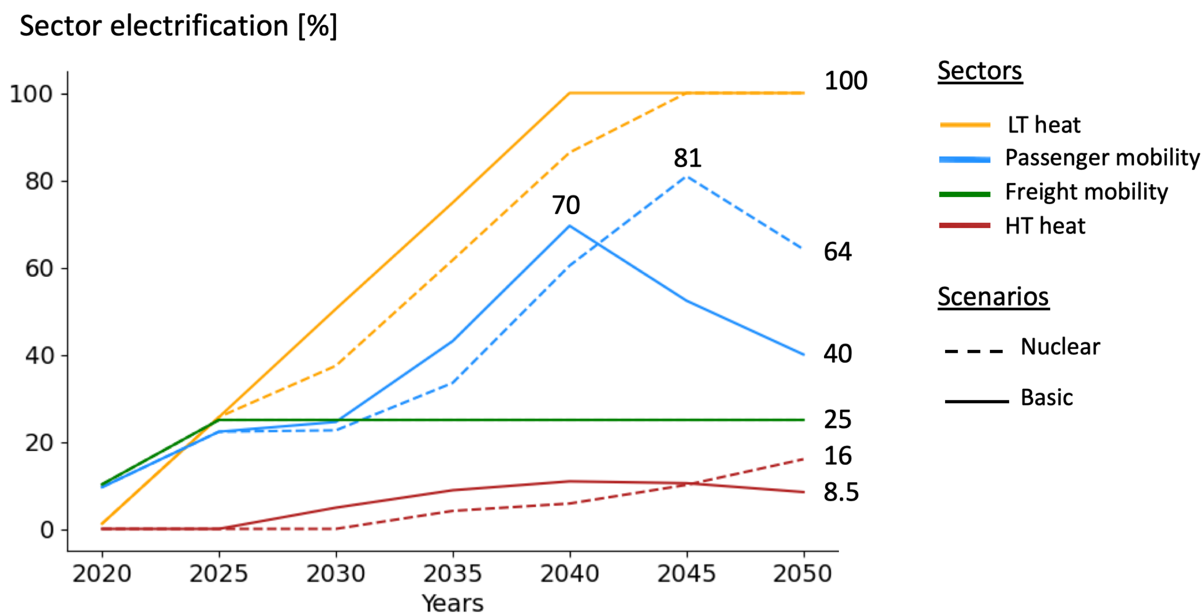

Figure 2.21: The different energy sectors are electrified more slowly in the nuclear scenario, except the freight mobility sector. Nevertheless, the passenger mobility and the HT heat are more electrified at the end of the transition. The electrification of a sector is the percentage of end-use energy produced in this sector by technologies consuming electricity. Abbreviations : low temperature (LT), high temperature (HT).

In conclusion, nuclear power plants decrease the total transition cost by 9% because nuclear energy is a cheap way to produce electricity. Nuclear power plants also allow to take more time to change the system into the sustainable energy system of 2050 as the installation of PV panels, the installation of offshore wind turbines and the electrification of the energy sectors can be slower. Consequently, the nuclear power plants available today could be a real asset to facilitate the Belgium energy transition and are compatible with a sustainable energy system since the emissions related to nuclear energy are minor.

2.3.2 Zero Imported Electricity scenario

The Zero Imported Electricity scenario is a scenario where Belgium would make the transition without importing electricity from neighbouring countries. This scenario is useful because there are two strong assumptions on the imported electricity in the EnergyScope Pathway model.

The first one is the carbon footprint of this electricity. In the model, the CO_2 emissions related to the imported electricity decreases during the transition until reaching carbon-neutral electricity imports in 2050. This comes from an assumption that the neighbouring countries, from where electricity is imported, will also transit towards a sustainable energy system by 2050.

The second assumption is its availability. In the model, the imported electricity is available at any time. The issue is that imported electricity is needed when solar and wind energy are low. It is likely that foreign countries, assumed to transit towards sustainability, will also face this problem during the same days as Belgium and will therefore not be able to sell electricity to Belgium.

The two assumptions are actually contradictory. Either electricity will be available when Belgium needs it but it will not be carbon neutral, or the opposite. This is why it is pertinent to model and analyse an energy transition where Belgium does not import electricity.

Figure 2.22 illustrates what technologies will be used in order to replace the electricity imported in the basic scenario. The best economical solution is to replace the imported electricity of the basic case by combined cycle gas turbines (CCGT) and industrial gas cogeneration of heat and power (CHP) between 2020 and 2040, and only by CCGTs between 2040 and 2050. CCGTs will use natural gas until 2050 when they would switch to synthetic natural gas. Consequently, 2.4 additional GW of industrial gas CHP is needed from 2025 to 2035 and the capacity of CCGTs needed in Belgium in 2050 would be 13.6 GW compared to 3.9 GW for the basic case.

Moreover, the total transition cost will increase by 5% compared to the basic scenario (912B€ vs 870B€). This also shows the utility that nuclear power plants could have in the Belgium energy transition. Nuclear power plants could substitute the imported electricity since 44 TWh/year of electricity can be produced from nuclear power plants and the maximum amount of electricity imported in the basic scenario is 32.4 TWh/year in 2050.

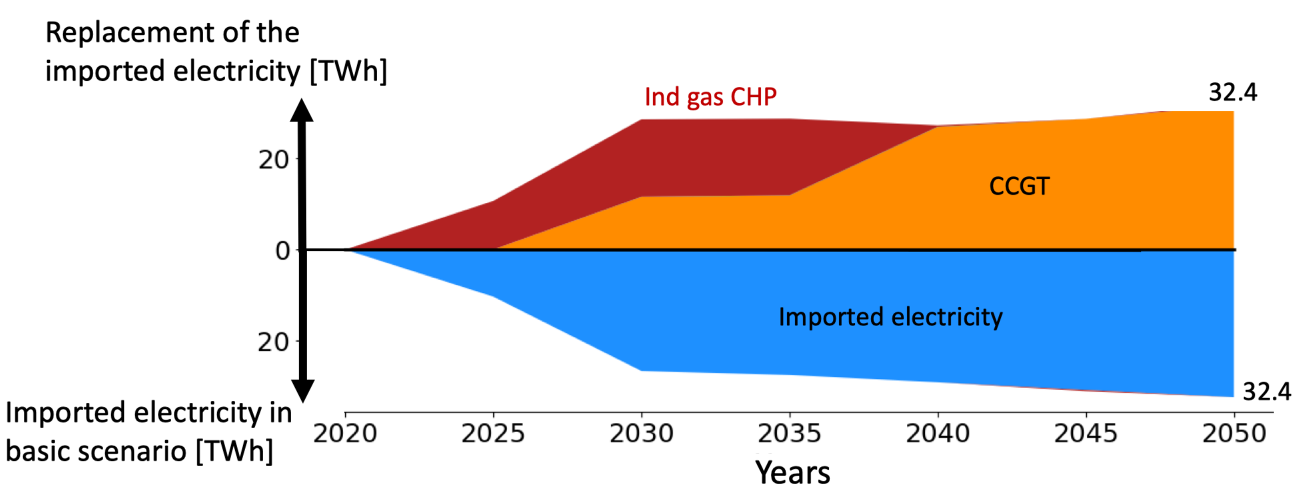

Figure 2.22: The most cost-effective way to substitute the imported electricity is with industrial gas cogeneration of heat and power (CHP) and combined cycle gas turbines (CCGT).

2.3.3 Phase budget scenario

The phase budget scenario is a scenario similar to the basic scenario except that the CAPEX of the phases must be constant during the transition. The model is however free to choose the constant phase CAPEX in order to minimise the total transition cost. The purpose of this scenario is to give an order of magnitude for a 5-year budget that the politicians could set to install new technologies required to transit towards a sustainable energy system in Belgium. The purpose is also to analyse how the energy transition will change if a constant budget is used.

Figure 2.23 shows the constant budget in this scenario compared to the CAPEX of the phases in the basic scenario. The optimal constant budget (i.e. the budget that minimises the overall transition cost) seems to be 95.15B€ per phase. In the basic scenario, the CAPEX decreases during the transition as the major investments are made in the beginning. If a budget needs to be respected, then the CAPEX of the phase 2020-2025 is too high. As a consequence, some technologies will have to be deployed later. This is mainly the case for photovoltaic (PV) panels and offshore wind turbines. The massive installation of those technologies is delayed by 5 years, as shown in Figure 2.24.

Moreover, since the PV panels installation is delayed by 5 years, less electrification of the system is needed during the transition. This results in a smaller electrification of the passenger mobility sector and of the high temperature (HT) heat sector during the transition, as shown in Figure 2.25. In the passenger mobility sector, the lower electrification results from fewer battery electric vehicles (BEV) deployed. The reason is that there is less need for the battery of those cars to cope with the electricity peak from PV panels as fewer PV panels are installed, compared to the basic scenario, from 2025 to 2040. In the high temperature (HT) heat sector, fewer industrial electric heaters are installed for the same reason, namely that less electricity from PV panels needs to be absorbed by the energy system in the middle of a sunny day.

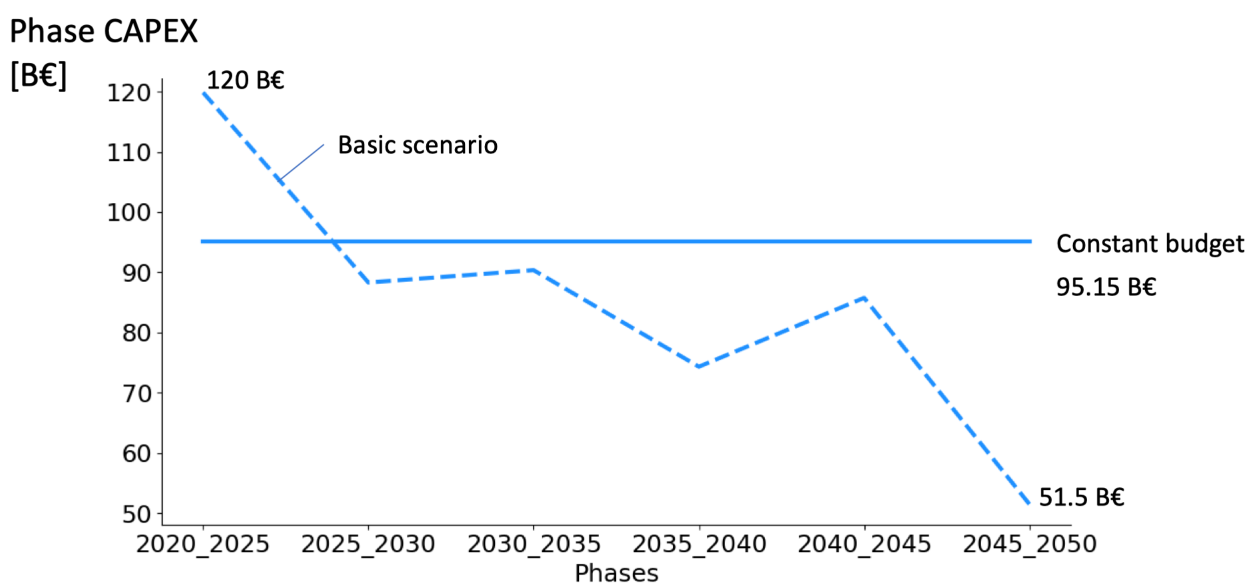

Figure 2.23: Capital expenditure (CAPEX) of the transition phases during the basic scenario and the phase budget scenario. In the phase budget scenario, the CAPEX of the phases must be constant. The optimal phase budget is 95.15B€ which is higher than the CAPEX of every phase in the basic scenario except the first one.

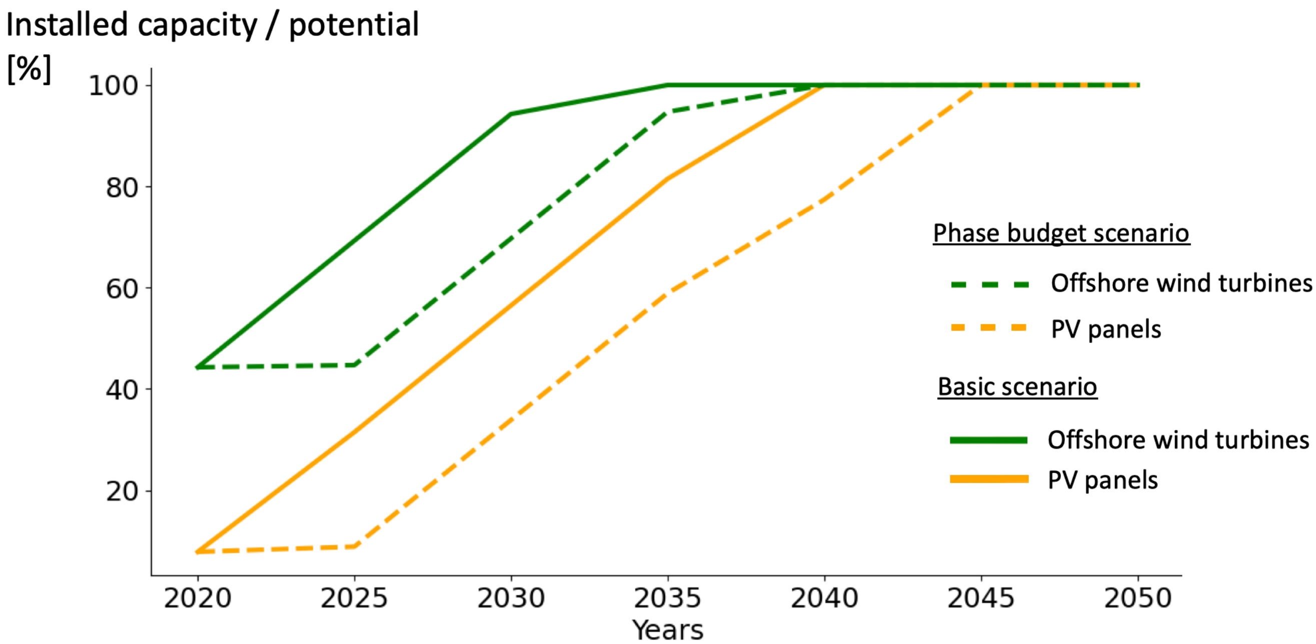

Figure 2.24: Installed capacity of offshore wind turbines and photovoltaic (PV) panels during the transition divided by their maximum potential in Belgium. The installation of offshore wind turbines and PV panels is delayed by 5 years in the phase budget scenario as the budget is too low to allow their installation between 2020 and 2025. During that period, it is preferred to install other technologies with the budget.

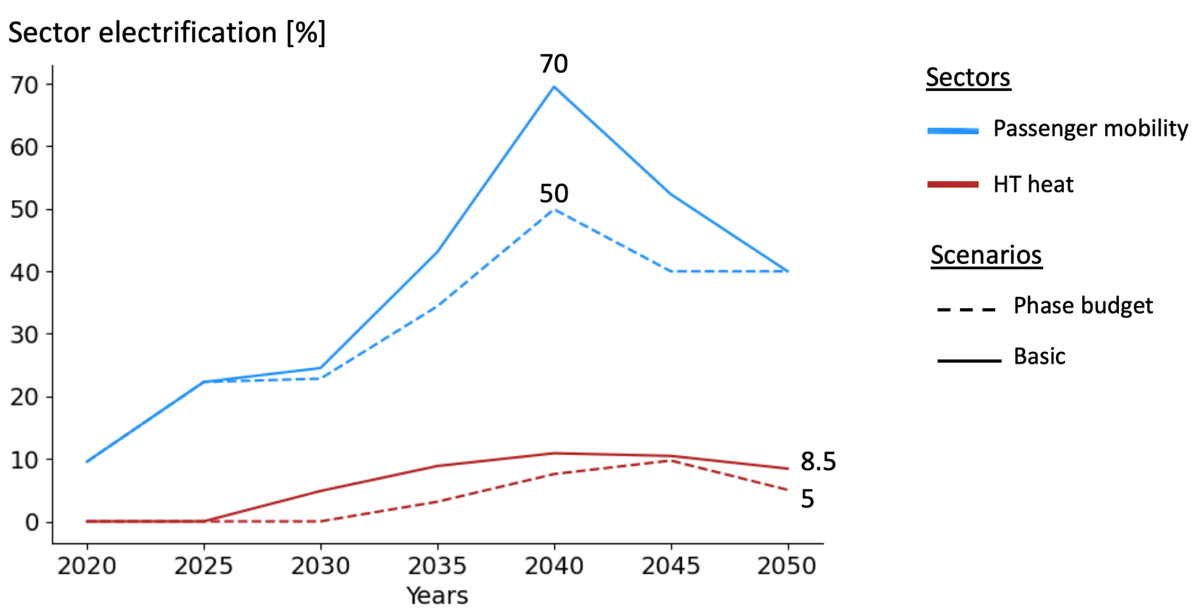

Figure 2.25: The electrification of a sector is defined as the amount of energy produced by technologies consuming electricity in the sector divided by the total energy produced in this sector. During the transition, the electrification of the passenger mobility sector and the high temperature (HT) mobility sector is lower in the phase budget scenario than in the basic scenario.

Chapter 3

Uncertainty quantification

In the EnergyScope Pathway model, the input parameters are fixed and assumed perfectly known. Nevertheless, in reality, every parameter is uncertain. There are two types of uncertainties: aleatory and epistemic. Aleatory uncertainties are due to the natural variation of a parameter and can not be decreased, while epistemic uncertainties are due to the lack of knowledge on the parameter and can therefore be decreased. We can take as an example the wind speed in a certain location. Wind speed varies naturally and could never be predicted with perfect precision, but we could measure the wind speed in that specific location to have more knowledge about it, and thus better predict it (i.e. decrease the epistemic uncertainty).

In his PhD thesis, Stefano Moret provides a detailed uncertainty characterisation for the parameters of the EnergyScope TD model [7]. This uncertainty characterisation was obtained with *a novel application-driven uncertainty characterization method for strategic energy planning problems*, developed by Stefano Moret [7]. This method characterises the uncertainty range of parameters using various different data in the literature. Appendix C presents the uncertainty characterisation he realised for the EnergyScope TD parameters and more details about his novel method. Moreover, because of the data scarcity, in the literature, on the probability density function of those parameters, the uncertain parameters are characterised by a uniform distribution with the range from Appendix C.

The parameter uncertainties must be propagated through the model in order to compute the uncertainty on the Belgium energy transition (i.e. its statistical moments). This will be realised using an uncertainty quantification (UQ) method which will use the uncertainty characterisation in Appendix C. Finding the statistical moments provides a more detailed picture than the over-conservative "worst-case scenario", often used in engineering cases. Indeed, in designing problems, worst-case analysis and safety factors are often used because of their simplicity of use. However, it often leads to over-designing. Taking into account uncertainties provides a true system optimisation and a more precise picture of the model output uncertainty. This is why, in this master thesis, a method computing the statistical moments of a model output is preferred.

The Uncertainties will be propagated through the Simplified EnergyScope Pathway model, and not through the EnergyScope Pathway model, to decrease the computational time required. As a reminder, the Simplified EnergyScope Pathway model is similar to the EnergyScope Pathway model but has a time step of 10 years instead of 5 and is therefore 5 times faster (as explained in section 1.3).

Moreover, it is also important that the chosen UQ method can provide a sensitivity analysis of the different uncertain parameters. There is two types of sensitivity analysis: a local sensitivity analysis (LSA) and a global sensitivity analysis (GSA). In a LSA, the parameters are varied one at a time, while, in a GSA, the parameters are varied simultaneously to take into account their synergies. However, more model evaluations are required to perform a GSA. Therefore, a LSA has a low computational time but does not take into account the interactions among the different parameters, whereas a GSA has a high computational time but takes into account those interactions.

In his PhD thesis [7], Stefano Moret reviewed multiple applications of sensitivity and uncertainty analysis methods to energy models. One of his conclusion is that global sensitivity analysis (GSA) methods are still limited in the energy field. LSA are generally preferred because of their lower computational cost. Nevertheless, in the case of an energy model or pathway model, there are interactions among the different parameters. Therefore, according to S. Moret, it is important to perform a GSA with energy models, instead of a LSA, in order to analyse correctly the influence of the parameter uncertainties. This is why the chosen UQ method will also perform a GSA in order to analyse which parameters drive the uncertainty on the energy transition cost.

Consequently, the purpose of this chapter is to analyse the uncertainty on the Belgium energy transition cost due to the uncertainties on the input parameters. The purpose is also to analyse what parameters drive this uncertainty to know where to focus on acquiring more knowledge to decrease the uncertainty on the Belgium energy transition.

In section 3.1, multiple potential UQ methods will be presented and compared in order to choose the most interesting one. Then, in section 3.2, the chosen UQ method (i.e. the polynomial chaos expansion method) will be described in more details. Finally, in section 3.3, the results of an uncertainty and global sensitivity analysis on the Belgium energy transition will be analysed. Results on the use of a polynomial chaos expansion method with an energy model will also be analysed.

3.1 Different uncertainty quantification methods

This section will briefly describe different UQ methods and will compare them according to the following criteria:

- **The model is considered as a black box :** Using the model as a black box means that the formulation of the model dos not have to change for the UQ method to work. The UQ method works only with the inputs and outputs of the model. In the case of the EnergyScope Pathway model, which is coded in AMPL, it will be much more convenient to use the model as a black box with a UQ method coded in something more common like python.
- **Number of evaluations required :** The Simplified EnergyScope Pathway explained above is still an expensive-to-evaluate model. An evaluation takes around 250 seconds. Therefore, the number of evaluations required to perform the UQ is crucial, as it will be illustrated.
- **Post-processing cost :** The post-processing cost is the computational cost required after the model evaluations are performed. For example, calculating the statistical moments is in the post-process and has a computational cost. A low post-processing cost will be preferred to reduce the overall computational cost.

3.1.1 Monte-Carlo method

The Monte-Carlo Method is an easy-to-implement method and is robust since convergence is always reached. The basic principle is to pick randomly the input parameters, according to their distribution, and evaluate the model output. To do this, the probability density function of each parameter needs to be specified. This is repeated until convergence is reached, meaning for example that for five successive iterations the difference between the mean and the cumulative mean, accounting for every iteration before the last one, is below a threshold (1% of the mean). Convergence could also be reached if the maximum number of iterations (fixed) is surpassed but the first criteria has not been validated yet. Then the data must be post-processed to calculate the statistical moments.

The Monte-Carlo Method has been commonly used with energy systems because of its simplicity of use [15–18]. Although this method is simple and robust, it is inefficient for expensive-to-evaluate models since it requires $10^4 - 10^6$ evaluations to ensure convergence, as pointed out in [19–21]. For example, the Simplified EnergyScope Pathway model that will be used for the uncertainty quantification (UQ) has an evaluation time of around 250 seconds. If 10^4 samples are needed for the UQ, it would take 29 days to compute the statistical moments of the Simplified EnergyScope Pathway output.

3.1.2 Latin Hypercube Sampling method and Sobol' sequences

An alternative to the Monte-Carlo method would be to use a more efficient sampling technique than Monte-Carlo. A famous one is Latin Hypercube Sampling (LHS). For example, Wang et al. used this method to do a robust optimisation of an energy system in Stockholm [22].

While Monte-Carlo sampling is based on pure randomness, Latin Hypercube Sampling aims at organising the random sampling. The principle of LHS is to divide the uncertain parameters into different intervals with equal probability and select a point in each interval. The points can be selected randomly in the interval or non-randomly (in the middle of the interval for example).

While in Monte-Carlo sampling many points are needed to ensure having the global feature of the output function, in LHS the global feature can be obtained with fewer points since we ensure to take points representing the entire distribution of the parameters. It allows finding the output distribution with fewer evaluations [22].

Other sampling techniques exist such as low discrepancy quasi-random sequence. According to S. Burhenne et al., *the discrepancy metric was defined by Ilya M. Sobol' and is the maximum deviation between the theoretical density* $d_t = 1/N$ *and the point density* d_i *in an arbitrary hyper-parallelepiped* (P_i) *within the parameter space (hypercube)* [23]. Having a low discrepancy means that the sample points will explore more the multi-dimensional space. The discrepancy in the exploration of the multi-dimensional parameter space is a good criterion to assess the performance of a sampling method (i.e. its ability to explore the multi-dimensional space) [23].

One example of low discrepancy quasi-random sequences is the **Sobol' sequences** [23,24]. Sobol' sequences provide a better space-filling than Monte-Carlo and Latin Hypercube Sampling [23,24]. Therefore, a sampling method based on Sobol' sequences will need fewer model evaluations than Monte-Carlo and Latin Hypercube Sampling to obtain the same accuracy.

Nevertheless, according to L. Chrisman [25], *when your model has multiple probabilistic inputs, the convergence rates for LHS start looking more like those for Monte Carlo.* Since the Simplified EnergyScope Pathway model has a lot of uncertain parameters, LHS will tend to have a similar order of computational cost as Monte-Carlo. Furthermore, M. Roberts show in [24] that for high dimensional problems, the Sobol' sequence is not guaranteed to be better than random sampling like Monte-Carlo because of the curse of dimensionality. Therefore, as an assumption, the number of model evaluations for the uncertainty quantification (UQ) with LHS and Sobol' sequences will be approximated as having the same order of magnitude as Monte-Carlo ($10^4 - 10^6$).

To conclude, when dealing with expensive-to-evaluate models, a sampling-based method, such as the three described above, is often not appropriate because it requires too many evaluations [19]. Instead, surrogate modelling has gained popularity in the last three decades as a solution for the uncertainty quantification of complex and expensive-to-evaluate models [20, 21, 26, 27].

3.1.3 Surrogate modelling

The principle of surrogate modelling is to fit a simplified model to the model response around a reference point. In other words, the purpose is to find a function $\hat{f}$ that approximates the function f (i.e. the model output). This surrogate/simplified model needs fewer model evaluations to be computed than the number of model evaluations needed for uncertainty quantification (UQ) with a sampling-based approach (e.g. Monte-Carlo, LHS, Sobol' sequences). This surrogate model is also much cheaper to evaluate than the model. Therefore, this surrogate model $\hat{f}$ can be used to approximate the model output of a set of samples and quantify the uncertainty of the model output at a lower cost than with a sampling-based approach.

A certain number of evaluations of the model is required to build the surrogate model. The points where the model must be evaluated are selected using a sampling technique. A couple of sampling techniques were described just above to use them as a UQ method, but they could also be used simply as a sampling technique for surrogate modelling. They will be used to select the points where the model must be evaluated, and then the surrogate model will be created with those evaluations. Afterwards, this surrogate model must be evaluated in many more points in order to find the distribution of the model output based on the distribution of the model inputs.

A type of surrogate modelling is Gaussian Process Modelling, also known as **Kriging** [28]. This method is well known for allowing the data to speak more for themselves. Indeed, in other surrogate models, a specific function is fit to approximate the response of the model. Nonetheless, in Kriging the approximation of the model response is more form-free. The model is evaluated in several points $(x_1, x_2, ..., x_n)$ with the corresponding model output $\mathbf{y} = (y_1, y_2, ..., y_n)$. Then a covariance function is used to obtain the impact of each evaluation on another point we want to estimate. This covariance function can then be used to approximate the output y_* of any points x_* [28].

An example of covariance function would be the "squared exponential" :

$$k(x, x') = \sigma_f^2 \, exp\left(\frac{-(x-x')^2}{2l^2}\right) + \sigma_n^2 \, \delta(x, x')$$

where σ_f^2 is the maximum allowable covariance, l is the length parameter, $\delta(x, x')$ is the Kronecker delta function to take care of the noise in the data, and σ_n another parameter.

The best estimate for the output y_* of a point x_* and the uncertainty of this estimate are respectively calculated as followed

$$\bar{y}_* = K_* K^{-1}\mathbf{y} \qquad \text{and} \qquad var(y_*) = K_{**} - K_* K^{-1} K_*^T$$

with

$$K = \begin{pmatrix} k(x_1, x_1) & k(x_1, x_2) & \cdots & k(x_1, x_n) \\ k(x_2, x_1) & k(x_2, x_2) & \cdots & k(x_2, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_n, x_1) & k(x_n, x_2) & \cdots & k(x_n, x_n) \end{pmatrix}$$

$$K_* = (k(x_*, x_1), k(x_*, x_1), ..., k(x_*, x_n)) \qquad K_{**} = k(x_*, x_*)$$

The drawback of this method is that some parameters of the covariance function need to be optimised. In the example above, we need to assign values to σ_f, σ_n and l. Since these parameters will change the results, they need to be chosen carefully. This is actually an optimisation problem that requires a multivariate optimisation algorithm and adds non-negligible post-processing cost [28].

Moreover, the kriging method suffers from the curse of dimensionality, meaning that the number of needed model evaluations increases exponentially with the number of uncertain parameters.

Another type of surrogate modelling is **Polynomial chaos expansion** (PCE) [29]. PCE is convenient to use with different energy systems [20, 21, 27, 30] and has a very small post-processing cost because the uncertainty quantification can be carried out directly after the construction of the surrogate model $\hat{f}$, as explained below.

The principle is to represent the model in an orthogonal basis of polynomial functions Ψ_i :

$$M(\xi) \approx \widehat{M}(\xi) = \sum_{i=0}^{P} u_i \Psi_i(\xi) \tag{3.1}$$

with M the real model output, $\widehat{M}$ the surrogate model output, $\xi = (\xi_1, \xi_2, ..., \xi_d)$ the independent uncertain parameters, and u_i the coefficient of the orthogonal polynomial Ψ_i.
The model is evaluated in several points. Then, those evaluations are used to find the unknown coefficients u_i by applying a least square minimisation.

One advantage of the PCE is that the approximated mean μ and variance σ^2 of the model can be calculated with the coefficients, without additional post-processing cost, as follows :

$$\mu = u_0 \qquad \sigma^2 = \sum_{i=1}^{P} u_i^2 \tag{3.2}$$

The higher moments could also be calculated using the coefficients u_i, but it is more costly because the number of terms increases exponentially. Furthermore, the mean and variance are sufficient to describe the output uncertainty for this application.

Another advantage of the PCE is that the global sensitivity analysis can be easily achieved by calculating the Sobol' indices with the coefficients u_i. For example, the total-order Sobol' indices quantifying the global sensitivity of an uncertain parameter on the output can be calculated as

$$S_i^{T,PC} = \sum_{\alpha \in A_i^T} u_\alpha^2 / \sum_{i=1}^{P} u_i^2 \qquad A_i^T = \alpha \in A | \alpha_i > 0 \tag{3.3}$$

Nevertheless, PCE suffers from the curse of dimensionality which is inconvenient with an expensive-to-evaluate model with a lot of input parameters. However, several solutions have been developed to counteract this when using a PCE. One of them is to use the sparsity of the different polynomials to decrease the number of model evaluations needed [31].

3.1.4 Other methods

Other methods exist to quantify the uncertainty of a model output. For example, Fuzzy programming and Bayesian approach seem to have good potential with expensive-to-evaluate functions and have been used several times with energy system models [32–35].

Nevertheless, in all the references cited above, those methods were implemented in the model itself and not around the model to use it as a black box which violate the first criterion to select the desired uncertainty quantification method. Because of the scarcity of literature on the use of fuzzy programming or Bayesian approach considering the model as a black box, those two methods are deemed inconvenient with the Simplified EnergyScope Pathway model.

3.1.5 Final choice

The comparison of the different methods with the different criteria is presented in Table 3.1. The PCE method is the chosen method to take uncertainties into account with the Simplified EnergyScope Pathway. Sampling-based methods require too many evaluations. The fuzzy programming and the Bayesian approach does not seem to consider the model as a black box. Finally, the PCE method has been chosen over the Kriging method because, in Kriging, there is an additional optimisation problem that increases the post-processing cost. Nevertheless, the PCE still suffers from the curse of dimensionality. Therefore, the use of sparsity will be required.

Table 3.1: Comparison of the different UQ methods according to important criteria. The criteria are presented in section 3.1. In this case, it is desired to consider the model as a black box, to require the fewer model evaluations as possible and to have a low post-processing cost.

Methods	Model as a black box	Number of model evaluations	Corresponding time[a]	Post-processing cost
Monte-Carlo	YES	$10^4 - 10^6$	29 - 2900 days	low
Latin Hypercube	YES	$10^4 - 10^6$ [b]	29 - 2900 days	low
Sobol sequencing	YES	$10^4 - 10^6$ [b]	29 - 2900 days	low
PCE	YES	10^3 [c]	3 days	low
Kriging	YES	O(PCE)[d]	$\sim$ 3 days	high
Fuzzy programming	NO	/	/	/
Bayesian approach	NO	/	/	/

[a]Time to evaluate the Simplified EnergyScope Pathway with the required number of model evaluations.
[b]Same order as Monte-carlo. This assumption is discussed in section 3.1.2
[c]Based on the uncertainty quantification conducted in section 3.3.2 with 34 uncertain parameters.
[d]This is an assumption that has been made because PCE and Kriging are two surrogate modelling methods, and it is not the number of evaluations that will distinguish the two methods in this case.

In the next section, the PCE method will be described in more details. For its further application, an open-source[a] PCE method, developed in python by Diederik Coppiters, will be used.

[a]Available through the following link : `https://rheia.readthedocs.io/en/latest/`

3.2 PCE method

The polynomial chaos expansion (PCE) is a method that can propagate uncertainties through a model $\mathcal{M}$, that follows the relation

$$y = \mathcal{M}(\boldsymbol{x}) \tag{3.4}$$

with y the quantity of interest (QoI) and $\boldsymbol{x} = (x_1, x_2, ..., x_M)^T$ the M inputs of the model. For example, in this master thesis, the model $\mathcal{M}$ is the Simplified EnergyScope Pathway, y is the Total Transition Cost and $\boldsymbol{x}$ is the vector of input parameters (e.g. technologies cost, resources cost, solar irradiance).

In reality, the input parameters are subject to uncertainties. The quantity of interest is a random variable Y that depends on the random input parameters $\boldsymbol{\xi}$:

$$Y = \mathcal{M}(\boldsymbol{\xi}) \tag{3.5}$$

Furthermore, even if all the input parameters of the model are subject to uncertainties, not all input parameters will be taken into account for the uncertainty quantification. This would be computationally too expensive. In this master thesis, some input parameters are considered uncertain and form the vector $\boldsymbol{\xi}$. The other parameters are fixed and assumed perfectly known.

3.2.1 Construction of the Polynomial Chaos Expansion

The PCE approximates the model response by a series of orthogonal polynomials Ψ_i [29], such that

$$M(\boldsymbol{\xi}) \approx \widehat{M}(\boldsymbol{\xi}) = \sum_{i=0}^{P} u_i \Psi_i(\boldsymbol{\xi}) \tag{3.6}$$

with $\widehat{M}$ the surrogate model, u_i the coefficients of the polynomials, $\boldsymbol{\xi} = (\xi_1, \xi_2, ..., \xi_d)$ the vector of independent uncertain parameters and d the number of uncertain parameters.

The orthogonal polynomials Ψ_i are multivariate polynomials because they can depend on multiple variables ξ_i. Those multivariate polynomials are a product of univariate orthonormal polynomials [29]:

$$\Psi_{\boldsymbol{\alpha}}(\boldsymbol{\xi}) = \prod_{i=1}^{d} \psi_{\alpha_i}^{(i)}(\xi_i) \tag{3.7}$$

with $\boldsymbol{\alpha} = (\alpha_1, ..., \alpha_d)$ a multi-indices (or a tuple) which is an ordered list of integers. A univariate polynomial $\{\psi_k^{(i)}, k \in \mathbb{N}\}$ is defined according to the statistical distribution of the i-th uncertain parameters. In this master thesis, all uncertain parameters follow a uniform distribution. Legendre polynomials are the polynomials used with uniform variables [29]. In addition, Legendre polynomials must be normalised, so that the univariate polynomials $\psi_{\alpha_i}^{(i)}$ form a Hilbertian basis:

Type of variables	Orthogonal polynomials	Hilbertian basis $\psi_k(x)$
Uniform $\mathcal{U}(-1, 1)$	Legendre $P_k(x)$	$P_k(x)/\sqrt{\frac{1}{2k+1}}$

Moreover, the index α_i of the univariate polynomial $\psi_{\alpha_i}^{(i)}$ represents the order of the Legendre polynomial. Therefore, the order of a multivariate polynomial $\Psi_{\boldsymbol{\alpha}}(\boldsymbol{\xi})$ is equal to the sum of the indices α_i of the tuple $\boldsymbol{\alpha}$.

The table above is for variables following a standardised uniform distribution. However, in practice, some variables follow a non-standardised uniform distribution. The random vector $\boldsymbol{\xi}$ must first be transformed into a set of reduced variables $\boldsymbol{U}$ through an isoprobabilistic transform [29]:

$$\boldsymbol{\xi} = \mathcal{T}(\boldsymbol{U}) \tag{3.8}$$

so that

$$\widehat{M}(\boldsymbol{\xi}) = \widehat{M} \circ \mathcal{T}(\boldsymbol{U}) = \sum_{i=0}^{P} u_i \Psi_i(\boldsymbol{U}) \tag{3.9}$$

Any variable ξ_i following a uniform distribution $\mathcal{U}(a, b)$ can be transformed into a variable U_i following a standardised uniform distribution $\mathcal{U}(-1, 1)$ as follows:

$$U_i = \frac{\xi_i - a}{b - a} \tag{3.10}$$

For the sake of simplicity, the stochastic parameter will still be designated by $\boldsymbol{\xi}$ in this master thesis, but this isoprobabilistic transform must be kept in mind when building a PCE.

In theory, an infinite series ($P = \infty$ in equation 3.6) will exactly represent the model but it is computationally intractable. Therefore, in practice, a truncated series is used [29]. The truncated series consists of all polynomials $\Psi_{\boldsymbol{\alpha}}$ up to a certain order p. It means that only the polynomials $\Psi_{\boldsymbol{\alpha}}(\boldsymbol{\xi})$ of order p or less are kept in the truncated series of order p. In other words, the truncated series is the following [29]:

$$\widehat{\mathcal{M}}(\boldsymbol{\xi}) = \sum_{\alpha \in \mathcal{A}^{d,p}} u_\alpha \Psi_\alpha(\boldsymbol{\xi}) \qquad \mathcal{A}^{d,p} = \{\boldsymbol{\alpha} \in \mathbb{N}^d \, : \, |\boldsymbol{\alpha}| = \sum_{i=1}^{d} \alpha_i \leq p\} \tag{3.11}$$

The number of polynomials is the number of tuples $\boldsymbol{\alpha}$ that respects the condition $|\boldsymbol{\alpha}| \leq p$, which is:

$$\text{card}\mathcal{A}^{d,p} = \binom{d+p}{p} = \frac{(d+p)!}{d!\,p!} \tag{3.12}$$

The number of polynomials depends on the order p of the PCE and on the number of stochastic parameters d. If we say that this number is equal to $P + 1$, then equation 3.11 is similar to equation 3.6. Moreover, the number of polynomials is also the number of coefficients u_i.

To compute the coefficients u_i of equation 3.6, a least square minimisation is applied as follows [29]. The QoI Y (see Eq. 3.5) can be represented by the following equation:

$$Y = \mathcal{M}(\boldsymbol{\xi}) = \sum_{i=0}^{P} u_i \Psi_i(\boldsymbol{\xi}) + \varepsilon \tag{3.13}$$

with ϵ the residual error (i.e. the error between the exact model and the PCE model). In order to determine the coefficients u_i, a sample set of points $\mathcal{X} = \{\boldsymbol{x}^{(i)}, i = 1, ..., n\}$, with $\boldsymbol{x}^{(i)} = (\xi_1^{(i)}, ..., \xi_d^{(i)})$, is created by a latin hypercube sampling (LHS) method or a Sobol' sequences method, presented in section 3.1.2. Then, the model is evaluated in each points of $\mathcal{X}$ and the results are stored in a vector

$$\mathbf{y} = \{y^{(1)} = \mathcal{M}(\boldsymbol{x}^{(1)}), ..., y^{(n)} = \mathcal{M}(\boldsymbol{x}^{(n)})\}^T \tag{3.14}$$

From Eq. 3.13, the vector $\mathbf{y}$ respects the following equation:

$$\mathbf{y} = \mathbf{A}\boldsymbol{u} + \boldsymbol{e} \tag{3.15}$$

with $\boldsymbol{e} = (\varepsilon_1, ..., \varepsilon_n)$ the vector of the residual errors and $\mathbf{A}$ the *information matrix* calculated as follows [29]:

$$\mathbf{A} = \{A_{ij} = \Psi_j(\boldsymbol{x}^{(i)}), \quad i = 1, ..., n, \quad j = 0, ..., P\} \tag{3.16}$$

A least square minimisation is then applied to obtain the coefficients u_i which minimise the mean square error:

$$\hat{\boldsymbol{u}} = \arg \underset{\boldsymbol{u} \in \mathbb{R}^{card\mathcal{A}}}{min} \frac{1}{n} \sum_{i=1}^{n} \varepsilon_i^2 \tag{3.17}$$

This results in solving the following equation [29]

$$\widehat{\boldsymbol{u}} = \{\widehat{u}_0, \widehat{u}_1, ..., \widehat{u}_P\}^T = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{y} \tag{3.18}$$

Consequently, the approximation $\hat{\mathbf{y}}$ of the model response and the residuals $\hat{\boldsymbol{e}}$ are:

$$\widehat{\mathbf{y}} = \mathbf{A}\widehat{\boldsymbol{u}} \qquad \widehat{\boldsymbol{e}} = \mathbf{y} - \hat{\mathbf{y}} \tag{3.19}$$

The number of needed samples to do the least square minimisation is at least $P + 1$ (i.e. the number of unknowns u_i). An empirical rule of thumb is to take 2 to 3 times more samples than P in order to avoid overfitting [29,31]. This occurs when the model fits well the provided samples but can not accurately predict the quantity of interest (QoI) of other points.

3.2.2 Curse of dimensionality

The number of samples, with the rule of thumb mentioned above, is

$$2\frac{(d+p)!}{d!\,p!} \tag{3.20}$$

which increase exponentially when the order p of the PCE or the number of uncertain parameters d increases, as shown in Figure 3.1 with the number of uncertain parameters d. Therefore, there is a trade-off between the accuracy of the PCE and the computational time. The higher the order p, the more precise the PCE is but the more computationally expensive it is to build (because more samples are needed).

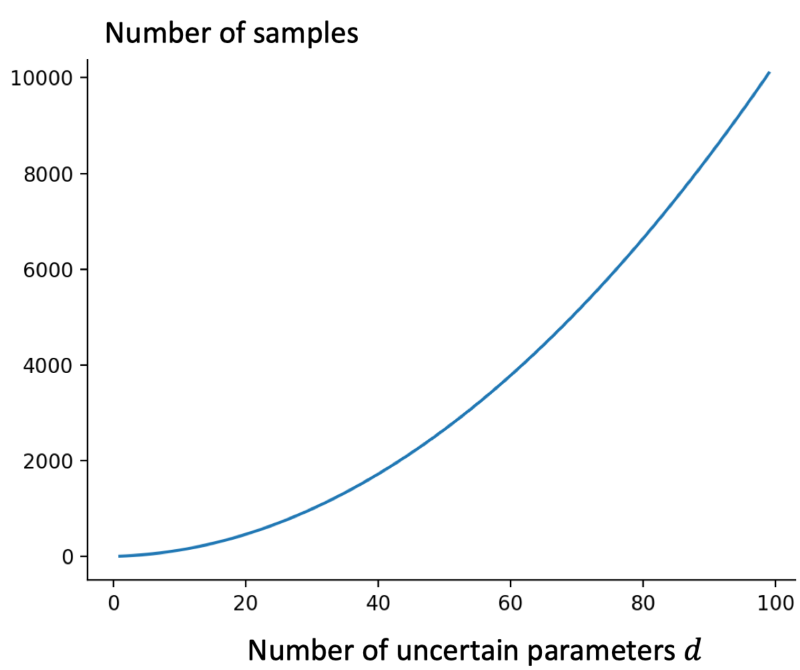

Figure 3.1: The number of samples increases exponentially with the number of uncertain parameters.

3.2.3 Leave-one-out error

The Leave-one-out (LOO) error of the PCE is a measure of the accuracy of the PCE to predict the quantity of interest (QoI) [29]. The idea behind the LOO error is to build a PCE with the provided samples where one point is set apart, and then evaluate the difference between the evaluation of the QoI in this point with the model and with the built PCE. For example, let's say that the point $\boldsymbol{x}^{(i)}$ is set apart from $\mathcal{X}$ and a PCE, denoted by $\widehat{M}^{\setminus i}$, built with the sample set $\mathcal{X}\setminus\boldsymbol{x}^{(i)}$. The predicted residual error is then

$$\Delta_i = M(\boldsymbol{x}^{(i)}) - \widehat{M}^{\setminus i}(\boldsymbol{x}^{(i)}) \tag{3.21}$$

The LOO error is then defined as

$$\widehat{Err}_{LOO} = \frac{1}{n}\sum_{i=1}^{n}\Delta_i^2 \tag{3.22}$$

Nevertheless, this would be computationally expensive since a PCE must be built for each point of the sample set $\mathcal{X}$. The LOO error can actually be computed using only one PCE. Indeed, it can be demonstrated that [29]

$$\Delta_i = M(\boldsymbol{x}^{(i)}) - \widehat{M}^{\setminus i}(\boldsymbol{x}^{(i)}) = \frac{M(\boldsymbol{x}^{(i)}) - \widehat{M}(\boldsymbol{x}^{(i)})}{1-h_i} \tag{3.23}$$

where h_i is the i-th diagonal term of matrix $\mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T$ and $\widehat{M}$ is the only PCE that must be built. In practice, a normalised version of the LOO error is used:

$$\widehat{\epsilon}_{LOO} = \frac{1}{n-P}\left(\frac{1+\frac{1}{n}\operatorname{tr}\mathbf{C}_{emp}^{-1}}{\mathrm{Var}[\mathcal{Y}]}\right)\sum_{i=1}^{n}\left(\frac{M(\boldsymbol{x}^{(i)}) - \widehat{M}(\boldsymbol{x}^{(i)})}{1-h_i}\right)^2 \tag{3.24}$$

with $\mathbf{C}_{emp} = \frac{1}{n}\Psi^T\Psi$ and $\operatorname{tr}(\cdot)$ the trace. A rule of thumb specifies that the PCE is a good surrogate model if $\widehat{\epsilon}_{LOO} < 0.01$ [29].

3.2.4 Post-processing

One advantage of the PCE is that, once the coefficients u_i are computed, the mean μ and standard deviation σ of the QoI can easily be calculated as

$$\mu = u_0 \tag{3.25}$$

$$\sigma^2 = \sum_{i=1}^{P} u_i^2 \tag{3.26}$$

Moreover, a global sensitivity analysis (GSA) can be realised with the coefficients u_i, and therefore without additional cost [29]. The purpose of a GSA is to quantify which input parameters or combinations of input parameters explain the most the variance of the QoI. This GSA can be carried out by calculating the contribution of the stochastic parameters to the variance. This contribution can be quantified through the Sobol' indices which are easily calculated with the coefficients u_i. The total-order Sobol' index S_i^T of the i-th stochastic parameter is calculated as follows

$$S_i^T = \sum_{\alpha\in\mathcal{A}_i^T} u_\alpha^2 / \sum_{i=1}^{P} u_i^2 \qquad \mathcal{A}_i^T = \{\alpha \in \mathcal{A}^{d,p} \mid \alpha_i > 0\} \tag{3.27}$$

and represent the total impact of a parameter on the variance of the QoI [29].

3.2.5 Stepwise regression method for building a sparse PCE

The PCE suffers from the curse of dimensionality, as explained previously. When increasing the number of uncertain parameters, the number of samples that must be evaluated by the model increases exponentially. Therefore, the number of uncertain parameters is limited by the computational time we can afford.

One solution to circumvent this issue is to build a sparse PCE instead of a full PCE. A full PCE is a PCE constituted of every polynomial Ψ_α with $\alpha \in \mathcal{A}^{d,p}$, as explained before. Whereas, a sparse PCE is only constituted of the most important polynomials to predict the QoI.

The idea behind a sparse PCE is that some multivariate polynomials Ψ_i are more important than others to predict the quantity of interest (QoI), just like some parameters have more impact than others on the QoI. Consequently, some multivariate polynomials could be removed, without influencing much the prediction of the QoI, and only the most important multivariate polynomials will be kept. By doing so, the PCE would be constituted by fewer multivariate polynomials, therefore fewer coefficients u_i should be calculated, which means that fewer sample points should be evaluated by the model. Consequently, the computational time can be significantly decreased.

In order to build such a sparse PCE, S. Abraham et al. developed and published in 2017 a *robust and efficient stepwise regression method for building sparse polynomial chaos expansion* [31]. This stepwise regression method will be used in this master thesis to build a sparse PCE instead of a full PCE when needed.

The flowchart of this stepwise regression method is represented in Figure 3.2. It is divided into three phases : an initialisation phase, a first forward step and a loop combining a forward-backward step [31].

The first phase is the initialisation phase. The model is evaluated in n samples, with n a user-defined constant depending on the available computational resources. The model outputs are then stored in a vector $\mathbf{y}$.

The next step is a first forward step, to add the first multivariate polynomial Ψ_i to the sparse PCE. All multivariate polynomials up to a user-defined degree p are part of a pool of candidate basis function Ψ_i. Each candidate basis function is assessed individually by building a one-predictor PCE for each Ψ_i. It means that if there are $P+1$ candidate basis function Ψ_i, then $P+1$ one-predictor surrogate models are constructed independently from each other:

$$\widehat{\mathcal{M}}_j(\boldsymbol{\xi}) = u_j \Psi_j(\boldsymbol{\xi}) \qquad j = 0, ..., P \tag{3.28}$$

with $\widehat{\mathcal{M}}_j$ the j-th one-predictor surrogate model. These one-predictor surrogate models are solved, i.e. the coefficients u_j are calculated with Eq. 3.18. The best candidate basis function Ψ_{j^*} is then found as follows [31]:

$$j^* = \text{argmax}_j \left\{ \frac{|\hat{u}_j|}{\sqrt{\mathbb{V}(\hat{u}_j)}} \, , \, j = 0, ..., P \right\} \tag{3.29}$$

with $\mathbb{V}(u_j)$ the variance of the coefficient u_j, which is also, by definition, the i-th diagonal term of the variance-covariance matrix of $\hat{\boldsymbol{u}}$ [31]:

$$\text{cov}(\hat{\boldsymbol{u}}) = \sigma^2 (\boldsymbol{A}^T \boldsymbol{A})^{-1} \tag{3.30}$$

with σ^2 the variance of the error.

Thereafter, the best predictor Ψ_{j^*} enters the surrogate model and is removed from the pool of candidate Ψ_i. The current residual $\hat{\boldsymbol{e}}_i$ is then updated using Eq. 3.19.

The last phase consists of a loop constituted of a forward step followed by a backward step. The forward step follows the same procedure as the first forwards step, aside from the fact that the one-predictor surrogate models are no longer fitted on the response $\mathbf{y}$ but on the current residual $\widehat{\boldsymbol{e}}_i$.

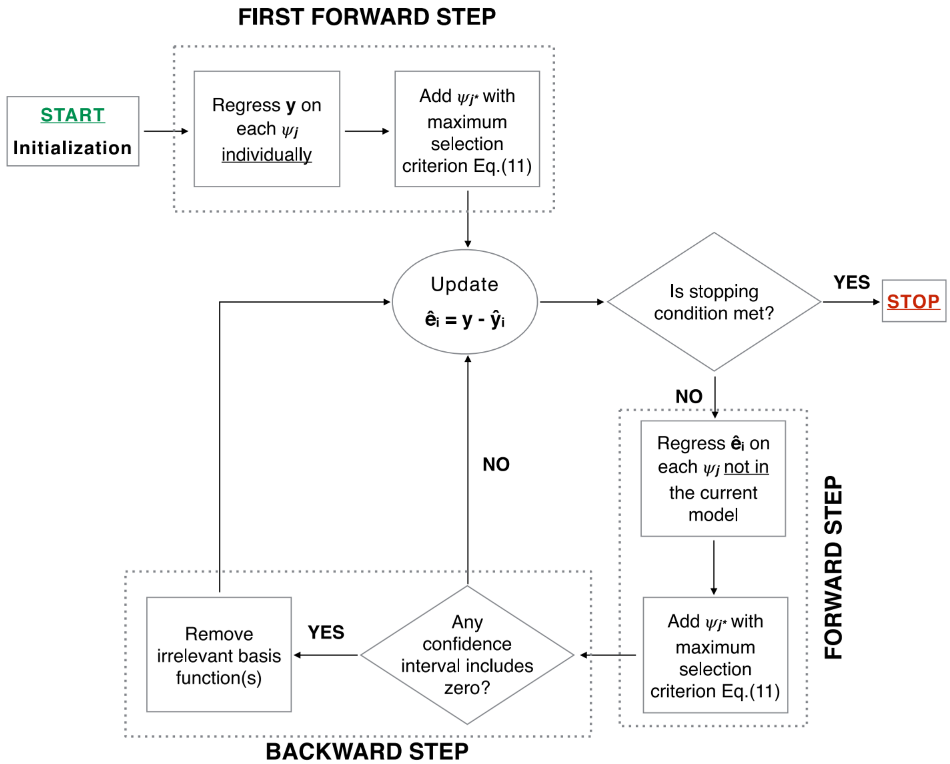

Figure 3.2: Flowchart of the stepwise regression method for building a sparse PCE. This Figure comes from the article written by S. Abrahams, et al. (2017) [31]. A first forward step determines the best multivariate polynomial and adds it to the sparse PCE. Then a loop of forward and backward step is realised to add the most relevant multivariate polynomials to the sparse PCE. When the stopping criterion is met, the sparse PCE contains the most important multivariate polynomials to approximate the response of the model of interest.

The backward step is then needed because the inclusion of a new polynomial Ψ_i to the surrogate model might affect the importance of the polynomials that are already in this surrogate model [31]. The backward step consists of calculating the confidence interval of the coefficients u_i, that are already in the surrogate model, with [31]:

$$u_i \in \left[\hat{u}_i \pm z_{[1-\alpha/2]} \sqrt{\mathbb{V}(\hat{u}_i)}\right] \tag{3.31}$$

where $z_{[1-\alpha/2]}$ is the $1-\alpha/2$ quantile of the standard normal distribution. In this master thesis, a 95% confidence level ($\alpha = 0.05$) will always be considered for this confidence interval (the same α was considered in the article of S. Abrahams, et al. [31]). If the confidence interval of a coefficient u_i includes zero, then the associated polynomial Ψ_i is removed from the current surrogate model.

After the forward and backward step, the current residual $\hat{\boldsymbol{e}}_i$ is updated using Eq. 3.13. This forward-backward step continues until a stopping condition is met. The stopping condition is met if the number of iterations reaches the number of samples evaluated by the model, or if the mean of the residual errors of the current iteration is below 0.01 or is equal to the same value during the last five iterations.

At the end of this stepwise regression method, the sparse PCE surrogate model is built with the most important polynomials Ψ_i to predict the response of the exact model.

3.3 Results

In section 3.3.1, the influence of the sparsity on the PCE accuracy, with an energy model, will be analysed. The purpose is to find which sparsity can be used to compute an accurate PCE with an energy model. Then, in section 3.3.2, an uncertainty analysis will be performed for the Belgium energy transition. The purpose is to analyse what is the uncertainty on the energy transition cost and what parameters are the main contributor to this uncertainty.

3.3.1 Sparse PCE accuracy with energy models

A stepwise regression method for building a sparse polynomial chaos expansion (PCE) was explained in section 3.2.5. This method constructs the most accurate PCE possible with the limited computational time we can afford. The purpose of this section is to analyse the influence of sparsity on the accuracy of the build PCE with an energy model.

The EnergyScope TD model is used to analyse the different sparsity as the Simplified EnergyScope Pathway model is computationally too expensive for this analysis. An analysis was performed with two sets of uncertain parameters, both accounting for the resources price and availability, the technologies price, the end-use demands and the renewable potential. One set is composed of 15 uncertain parameters and the other one of 31 uncertain parameters. The set of 31 uncertain parameters is actually a more detailed set but the same input parameters are changed in the model in both sets. As an example, in the set of 15 uncertain parameters, one parameters c_op_local represents the uncertainty on the price of local resources such as biomass, waste and coal. All those local resources price depend on this parameter. Whereas, in the set of 31 uncertain parameters, the parameters c_op_local is divided into 3 parameters : c_op_biomass, c_op_waste and c_op_coal. Therefore, the same parameters are varied in both sets but, in the set of 31 uncertain parameters, more synergies between the uncertain parameters will be taken into account.

In order to analyse the influence of sparsity, an uncertainty quantification on the EnergyScope TD model was performed for both sets of uncertain parameters and for different levels of sparsity, going from 90% of sparsity to a full PCE. As a reminder, a sparsity of 90% means that the model is evaluated 90% less times than to build a full PCE.

Figure 3.3 shows the influence of the sparsity on the mean and variance of the model output (i.e. the total cost of the energy system). From those results, a sparse PCE with a sparsity of 60% or less gives an accurate approximation of the mean and variance, as the error made compared to a full PCE is below 1%. This means that, to compute an accurate approximation of the mean and variance of the model output, the model could be evaluated 60% less times than for a full PCE.

Furthermore, the influence of the sparsity on the LOO error is shown in Figure 3.4. With both sets of parameters, the LOO error decreases with sparsity. However, interestingly, the LOO error of any sparse PCE with the set of 31 uncertain parameters is lower than the LOO error of a full PCE. It means that any sparse PCE with that set of uncertain parameters will more accurately predict the model output than a full PCE. This result may be due to some noise in some polynomials of the full PCE. A sparse PCE is only composed of the most important polynomials as explained earlier. It is possible that the other less important polynomials, depending therefore on the less impacting uncertain parameters, are wrong about the weight of those parameters on the model output. If it is the case, then those parameters would just be noise to the prediction of the model output by the PCE. A sparse PCE will therefore eliminate that noise and thus predict more accurately the model output. No similar results were found in the literature, but this explanation was discussed with D. Coppitters which is familiar with the use of PCE on energy models as he is an author of multiple papers on this domain [20, 21, 27]. He confirmed that this result can happen for some uncertainty quantification on energy models for the explained reason. This would also explain why this results stands for the set of 31 uncertain parameters but not for the set of 15 uncertain parameters. Since the small set represents the same model parameters, but one uncertain parameter stands for multiple model parameters, then the uncertain parameters influence more the model output and this influence can therefore be easier detected and modelled by the PCE.

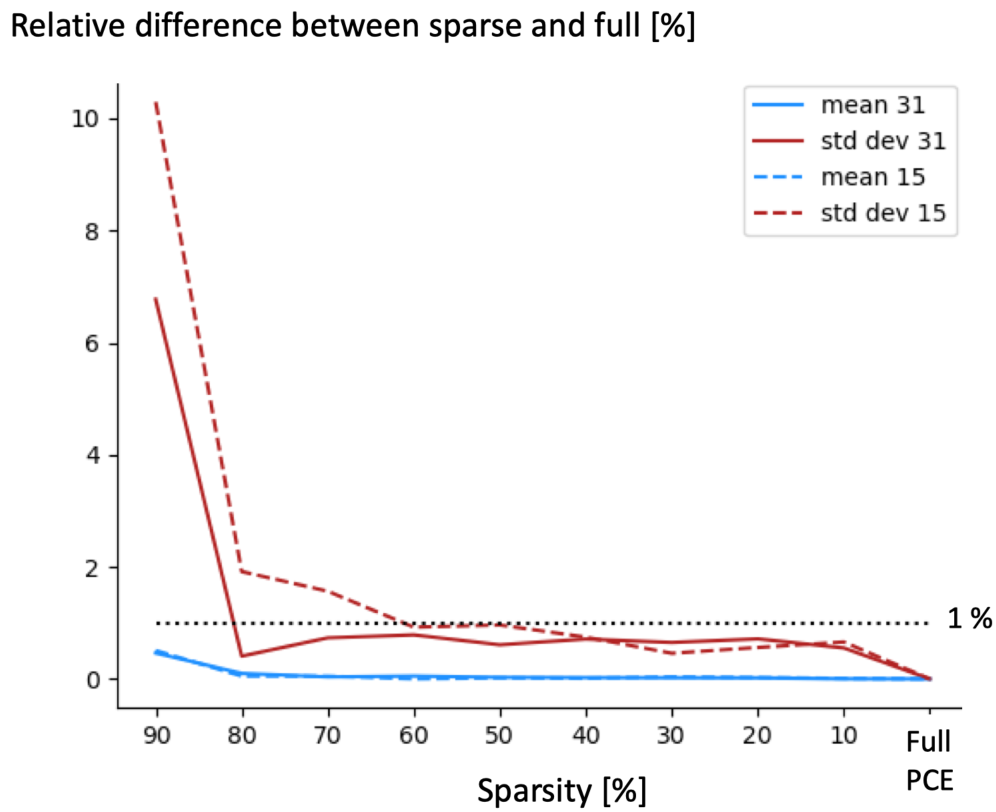

Figure 3.3: Difference between the mean and standard deviation when using a certain level of sparsity for the PCE or a full PCE. Two sets of uncertain parameters were used : one of 15 and one of 31 uncertain parameters. If a sparsity of 60% or less is used, then the error on the mean and standard deviation is below 1% compared to the ones with a full PCE.

With the set of 31 uncertain parameters, the LOO error is always over 0.01, which does not respect the rule of thumb that a PCE predicts accurately the model output if its LOO error is below 0.01. However, the PCE could be deemed accurate enough as a compromise between the PCE accuracy and the computational time required. In order to build a more accurate PCE, a higher order should be used. In this case, increasing the pce order by one would require 11 times more model evaluations which is not affordable. One could say that with the computational time he can afford, a PCE with a LOO error below 0.2 or 0.3 could be accurate enough.

Moreover, with the set of 31 uncertain parameters, from a sparsity of 50%, the LOO error remains constant at 0.013. Therefore, it would be useless to take a sparsity lower than 50%. Consequently, depending on the affordable computational time, sparsity can be used but it is not necessary to go below 50% even if it is affordable as the prediction of the model output will be similar.

In conclusion, when the mean and variance of the model output are the value of interest, up to 60% sparsity can be used. However, when the prediction of the model output is of interest, the PCE could not predict accurately the model according to the rule of thumb. In that case, it is up to the decision-maker to make a compromise between the accuracy of the PCE and the computational time.

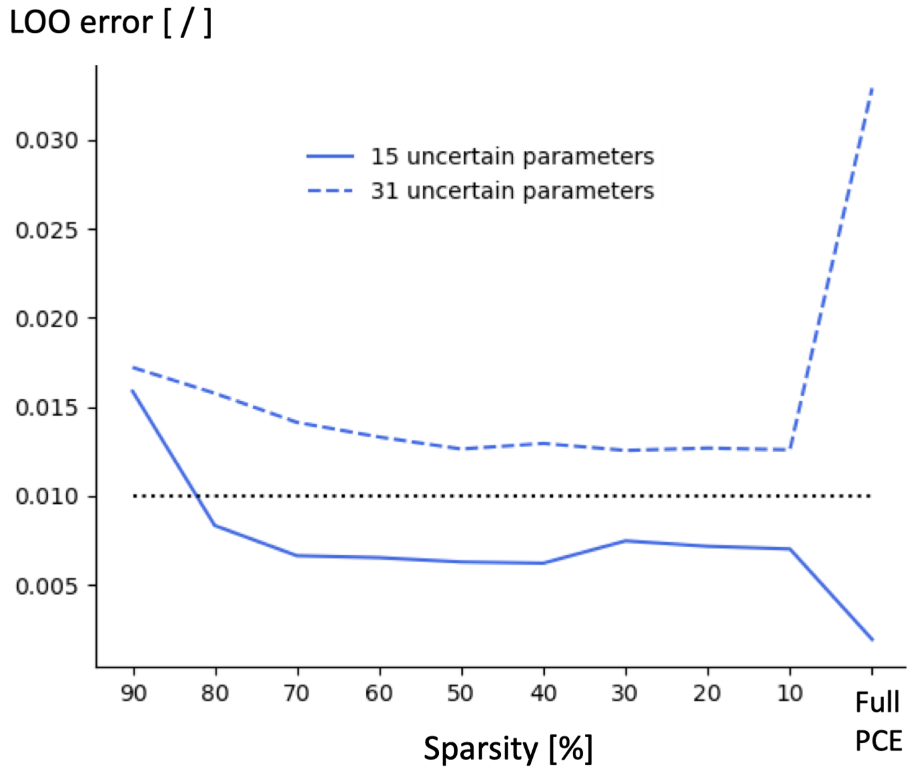

Figure 3.4: Leave-one-out (LOO) error depending on the level of sparsity of the PCE and on the number of uncertain parameters.

3.3.2 Uncertainty analysis on the Belgium energy transition

34 uncertain parameters ξ_i are taken into account for the uncertainty analysis with the Simplified Energy-Scope Pathway model and the PCE method explained above. A focus was made on the resources price and availability, the technologies price, the renewable potential, the end-use demands (EUDs), the technologies efficiency and the availability of solar and wind. The list of the 34 uncertain parameters taken into account can be found in Appendix C.2.

First, let's focus on the sensitivity analysis of the uncertain parameters on the phase costs. As a reminder, the cost of a phase is the sum of the OPEX and CAPEX cost of that phase (see Eq. 1.3 and 1.7). The sensitivity analysis is performed by computing the total Sobol' indices (see Eq. 3.27) of the uncertain parameters for each phase cost. As a rule of thumb, a parameter is deemed important if its total Sobol' indice, during at least one phase, is bigger than 1 divided by the number of uncertain parameters. Figure 3.5 shows the total Sobol' indices of the most influencing parameters for each phase. Those parameters are described in Table 3.2.

Between 2020 and 2030, the uncertainty of the phase costs is mostly due to the uncertainty of the fossil fuel prices with the parameters $c\_op\_fossil\_other$ and $c\_op\_fossil\_car$. During this phase, the system is still based on fossil fuels (62% in the basic scenario of section 2.2) which explains this high dependence. Moreover, the uncertainty on the cost of the 2020_2030 phase also depends on the characteristics of old technologies, such as the price of old transport technologies and the efficiency of mature and standard technologies. It illustrates that the system is still based on old technologies since it is the beginning of the transition.

Table 3.2: Description of the parameters that contribute the most to the uncertainty on the energy system cost during the phases.

Parameter name	Description	Uncertainty range from nominal value
c_op_fossil_other	price of natural gas (NG), liquid fuel oil (LFO) and uranium	[−47.3% ; 89.9%]
c_op_fossil_car	price of diesel and gasoline	[−47.3% ; 89.9%]
c_op_elec	price of imported electricity	[−47.3% ; 89.9%]
c_op_synfuels	price of hydrogen (H_2), synthetic natural gas (SNG) and synthetic liquid fuel (SLF)	[−47.3% ; 89.9%]
c_inv_TR_old	price of new technologies for passenger and freight mobility	[−21.6% ; 21.6%]
c_inv_TR_new	price of old technologies for passenger and freight mobility	[−39.6% ; 39.6%]
eff_mat_std	efficiency of mature and standard[a] technologies	[−5.7% ; 5.7%]
eff_new_std	efficiency of new and standard[a] technologies	[−20.8% ; 20.8%]
EU_I	industry end-use energy demand	[−10.5% ; 5.9%]

[a]A technology is classified as mature or new based on its stage of development and is classified as standard or custom based on its level of customisation. For example, a fossil fuel boiler is a mature and standard technology as the technology is well-known nowadays and it is not a customised good. On the contrary, a hydrogen car is a new and customised technology.

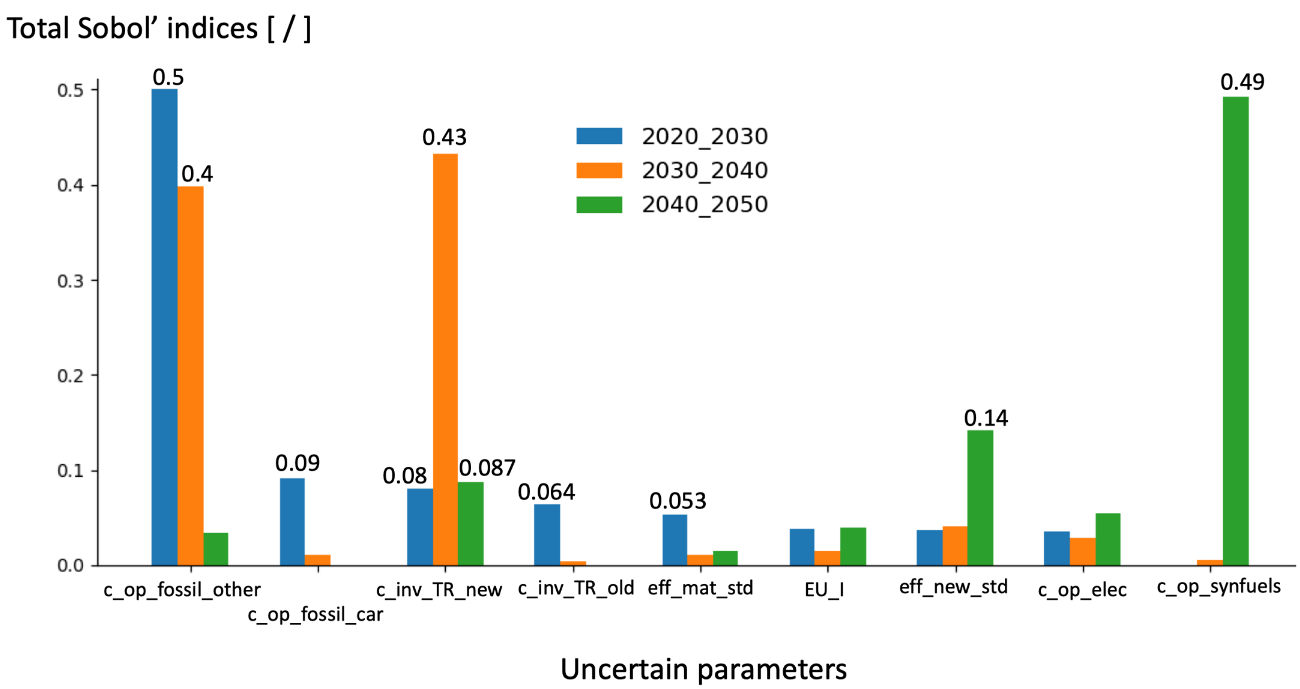

Figure 3.5: Total Sobol' indices of the parameters contributing the most to the uncertainty on the energy system cost during the transition phases. Total Sobol' indices are calculated with equation 3.27. From 2020 to 2050, the most contributing parameters switch from fossil fuels and old technologies to new technologies and resources.

Between 2030 and 2040, the uncertainty cost is mainly due to the uncertainty on the price of fossil fuels other than diesel and gasoline, and on the investment cost of new transportation technologies. This means that fossil fuels are still a major part of the energy system between 2030 and 2040. It is coherent with the analysis of the basic scenario in section 2.2 where natural gas (NG) is the main resource used during that phase. However, the mobility sector makes its transition towards sustainability between 2030 and 2040 as the model invests in new transport technologies during that phase.

Between 2040 and 2050, the uncertainty cost is mainly due to the uncertainty on the synthetic fuels price. As explained in section 2.2, from 2040 the remaining fossil fuels are substituted by synthetic fuels to decrease the CO_2 emissions. Moreover, the price of new transport technologies and the efficiency of new and standard technologies also drive the uncertainty of the 2040_2050 phase cost. It means that between 2040 and 2050, the energy system is based on new technologies and resources.

Moreover, the imported electricity is contributing to the uncertainty on the energy system cost during multiple phases. Firstly, electricity is imported during the entire transition as explained in the basic scenario analysis in section 2.2. Secondly, the price of imported electricity has a high uncertainty range (see Table 3.2). This explains the significant contribution of the uncertainty on the imported electricity price.

From this uncertainty quantification, the 99% confidence interval for the phase costs was computed and is shown in Figure 3.6. The energy system cost decreases with time because of two reasons. Firstly, 1€ today is worth more than 1€ in 2050. Secondly, the cost of the new technologies installed during the transition is assumed to decrease with time because more knowledge on them will be available.

On the other hand, the uncertainty on the cost of the phases increases with time as the 99% confidence interval grows from a range of 101 B€ in 2020-2030 to a range of 173 B€ in 2040-2050 (see Fig. 3.5). The uncertainty range from the nominal value is therefore $\pm12.7\%$ in 2020-2030 and increases to $\pm38.5\%$ in 2040-2050. This proves that uncertainties are important on the Belgium energy transition cost and must be taken into account.

The first reason is that the prices of the fossil fuels used nowadays have a wider range of uncertainty than the price of synthetic fuels that must be used in the future. Indeed, fossil fuels price and synthetic fuels price have the same percentage of variation from their nominal value (see Table 3.2) but synthetic fuels are more expensive than fossil fuels which result in a wider range of uncertainty.

The second reason is that the price of the technologies used today is less uncertain than the price of the new technologies deployed during the transition. The uncertainty on the energy system cost will consequently increase as new technologies substitute old technologies during the transition.

To conclude, this analysis gives a clue on what uncertainties are the most important to decrease to add robustness to the Belgium energy transition. The focus should be to decrease the uncertainty on the new technologies, and especially the new transport technologies, by acquiring more knowledge on fuel-cell transport, electric transport and natural gas transport for example. This will decrease significantly the uncertainty on the cost of the transition phases since the uncertainty on those technologies is one of the main drivers.

The focus should also be to decrease the uncertainty on fossil fuels and synthetic fuels as they are strongly influencing the uncertainty of the phase costs. However, the prices of imported fuels are difficult, if not impossible, to predict. In his PhD thesis [7], S. Moret illustrates that the forecasts on fossil fuel prices were overestimated by a factor of 2.95 in 2005. Consequently, decreasing the uncertainty on the imported fuels will be complicated. Nevertheless, there is one way to decrease the uncertainty on synthetic fuel prices: produce them locally. The problem with that is there is not enough available local resources to produce the amount of synthetic fuels needed for the Belgium energy transition, as analysed in the last chapter. Decrease the uncertainty on the fossil and synthetic fuel prices will therefore be more complicated than decrease the uncertainty on the new technologies cost.

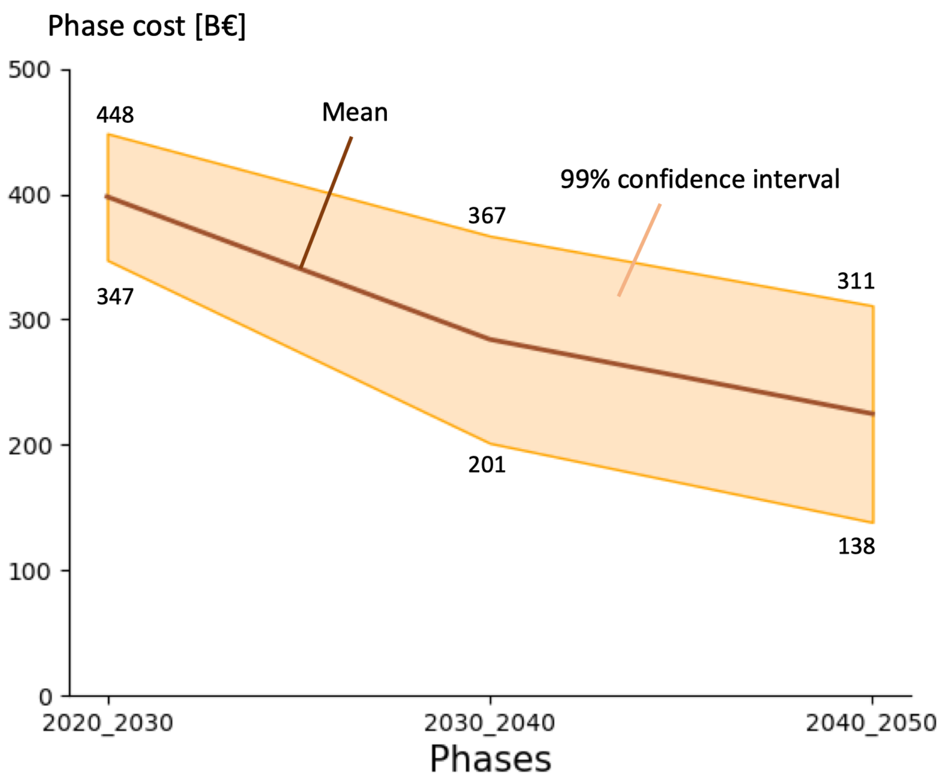

Figure 3.6: Mean and 99% confidence interval of the cost of the transition phases. The cost of the phases decreases during the transition but the uncertainty of the cost of the phases is increasing during the transition as the confidence interval becomes larger with time.

Chapter 4

Robust optimisation

The total transition cost is very sensitive to uncertainties as illustrated in the last section. This means that the deterministic energy transitions analysed in chapter 2 could be fragile. A fragile optimum is an optimum where a slight variation of the input parameters could drastically increase the objective function. This optimum is therefore strongly influenced by the input parameter uncertainties. In opposition to a fragile optimum, a robust optimum is an optimum little influenced by uncertainty. A fragile energy transition is an issue because the goal is to transit optimally towards a sustainable energy system whatever the uncertainties. The best energy transition is a transition that minimises the total transition cost and is little influenced by uncertainties to ensure that the total transition cost will not vary much from what is expected.

In order to find such an energy transition, both the mean and the variance of the total transition cost need to be minimised. This results in a multi-objective optimisation problem. Multiple methods exist to solve a multi-objective optimisation problem. In their work, G. Chiandussi et al. describe different methodologies for multi-objective optimisation [36].

Moreover, in a multi-objective optimisation problem, improving one objective is often done at the expense of others. As a consequence, the solution of a multi-objective optimisation problem is not one best solution but a Pareto front of the best solutions. The Pareto front is constituted of points that minimise both the mean and variance but are a trade-off between these two objectives, as it will be illustrated later.

In his PhD thesis [7], S. Moret reviewed applications of robust optimisation to energy models. Based on his review, he concluded that robust optimisations of energy systems are still limited. Robust optimisations are typically limited to specific cases or sectors (often the electricity sector) and consider only a subset of parameters. In general, this is due to the difficulty to incorporate uncertainties in the complex formulation of the deterministic model. In response to that, S. Moret developed *a novel robust optimisation framework for strategic energy planning* [7]. However, his robust optimisation framework is realised by changing the formulation of the energy model. In practice, it would be much more convenient to use a framework that considers the energy model as a black box. This framework could therefore be easily used with any model.

Moreover, the energy models reviewed in S. Moret's PhD thesis are snapshot models and not pathway models. As it was explained at the beginning of chapter 1, a snapshot model optimises the energy system over a year or a certain period of time, whereas a pathway model optimises the overall energy transition from the current energy system to the energy system of a target year. Literature on robust optimisations of energy pathway models is actually scarce. The reason might be that energy pathway models are generally expensive to evaluate and therefore not suitable for robust optimisation.

Two applications were still found. N. Zhao and F. You used a data-driven multistage adaptive robust optimisation approach with machine-learning to perform a robust optimisation on the New York State's electricity transition planning [37]. However, the robust optimisation is performed only on the electricity sector which hides the synergies with the heat and the mobility sectors. Moreover, C. Nicolas et al. analysed robust energy transition pathways for global warming targets [38]. However, the model they used is the TIMES Integrated Assessment Model (TIAM-Word) which is based on the TIMES model. This TIMES model optimises only the investment cost and not the hourly operation according to the energy models review performed by G. Limpens [6].

Consequently, the literature review shows the need for a methodology to perform a robust optimisation of an energy transition pathway model, considered as a black box if possible. Therefore, a novel robust optimisation framework has been developed in order to identify the technologies that make the energy transition more robust. The robust optimisation framework aims at performing a robust optimisation of an expensive-to-evaluate model and managing the curse of dimensionality. It will be illustrated that it is complicated to do but not totally impossible.

In section 4.1, the robust optimisation framework will be presented. Then, in section 4.2, results on robust optimisations of the Belgium energy system will be analysed. The robust optimisation framework was able to identify some robust technologies in some sectors, but it will be illustrated that the curse of dimensionality is difficult to manage when performing a robust optimisation on an energy pathway model.

4.1 Robust optimisation framework

The robust optimisation framework must optimise both the mean and variance of the total transition cost in order to build the Pareto front of these two objectives. Figure 4.1 illustrates a typical Pareto front that could be obtained as an example. The Pareto front is constituted of points that can not be surpassed. It means that there is no point with a lower mean and a lower variance than any points in the Pareto front.

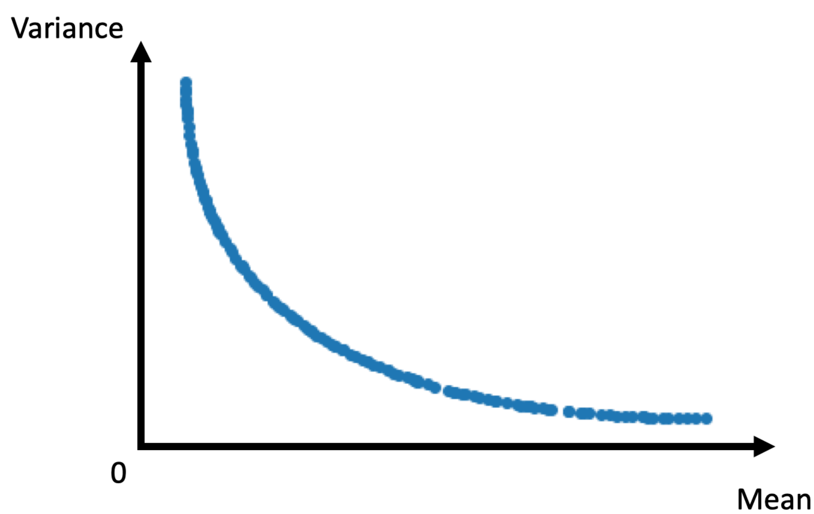

Figure 4.1: Typical Pareto front that could be obtained. The Pareto front illustrates the trade-off between the two objectives: if one objective needs to be lowered, then the other objective will increase. No point is better than another, it is on the user to chose which point is better for his application.

One of the most popular multi-objective optimisation algorithm that builds a Pareto front of the objectives is the nondominated sorting genetic algorithm II (NSGA-II) [39]. To build the Pareto front, this algorithm uses a population of individuals. An individual is a point whose coordinates are the decision variables of the optimiser. The purpose of NSGA-II is to find the decision variables that minimises both the mean and the variance to build the Pareto front. This is done by reiterating a five steps method until the Pareto front is found or the user wants the process to stop [39]. Those five steps basically consist of evaluating the objectives of each individual, keeping the best individuals and finally applying a genetic algorithm (GA) to complete the population with new and better individuals. This process is iterated a number of times (user-choice) to find the Pareto front. For the sake of simplicity, an open-source constrained NSGA-II code[a] has been used. A constrained NSGA-II is a NSGA-II where the decision variables are subject to constraints. It will be explained later why some constraints are required.

For the NSGA-II to work, the mean and variance of the total transition cost must be evaluated with the decision variables of each individual. This will be done by using a polynomial chaos expansion (PCE) as it was done in the previous chapter.

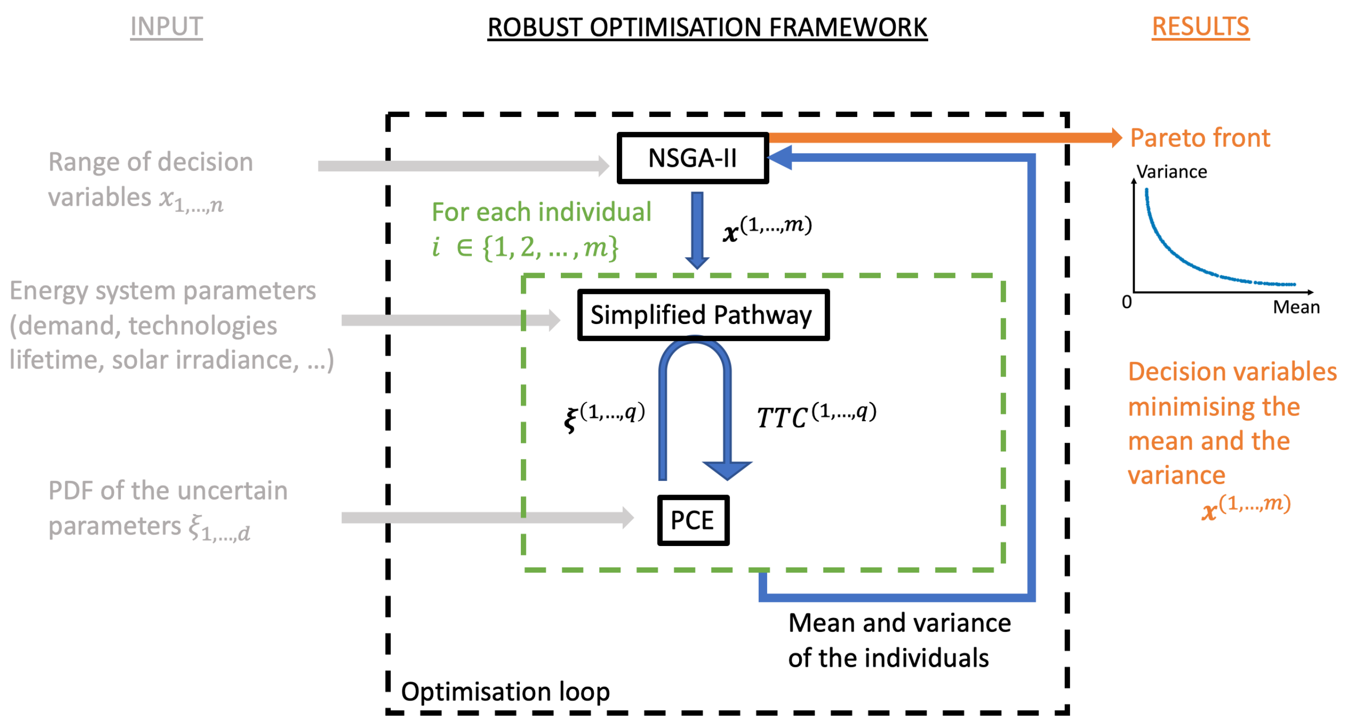

Figure 4.2: Ideal version of the robust optimisation framework. The robust optimisation framework optimises a population of m individuals. Uncertainty quantification is performed for each individual to compute its mean and variance with its corresponding vector of decision variables $\boldsymbol{x}$ (dotted green frame). Then, the multi-objective optimisation algorithm NSGA-II performs its five steps method to fill the population with better individuals. The process is then reiterated as much time as the user wants. In the end, the individuals form a Pareto front of the mean and variance of the total transition cost. Abbreviations : polynomial chaos expansion (PCE), total transition cost (TTC).

The robust optimisation framework is presented in Figure 4.2 and works in the following way. The population of NSGA-II is composed of m individuals and each individual is a point in the decision variables space:

$$\boldsymbol{x}^{(i)} = (x_1^{(i)}, x_2^{(i)}, \dots, x_n^{(i)}) \qquad i \in 1, \dots, m \tag{4.1}$$

with m the number of individuals and n the number of decision variables. For each individual i, its mean and variance are computed by first fixing its decision variables ($\boldsymbol{x}^{(i)}$) in the Simplified EnergyScope Pathway. As

[a]Can be found at : `https://github.com/yansen96/NSGA-II`

an example, let's say that the decision variables are the installed capacity of photovoltaic (PV) panels in 2030 (x_1), in 2040 (x_2) and in 2050 (x_3). If the i-th individual is characterised by the following vector of decision variables $\boldsymbol{x}^{(i)}$ =(10GW, 30GW, 20GW), then the capacity of PV panels in the Simplified EnergyScope Pathway is fixed to 10GW in 2030, 30GW in 2040 and 20GW in 2050.

Afterwards, an uncertainty quantification is performed for the i-th individual in the same way as it was explained in the last chapter: the Simplified EnergyScope Pathway is evaluated in a number q of uncertain parameters samples $\boldsymbol{\xi}$. Then, the total transition cost TTC of each uncertain parameters sample is used to construct a PCE, as described in section 3.2.1. The mean and variance of the total transition cost with the decision variables of the i-th individual are directly computed from the constructed PCE with equation 3.25 and 3.26. This process is performed for each individual independently. Afterwards, the population is changed by NSGA-II which tries to found better sets of decision variables, as explained before. Then, this new population follows the exact same steps. This optimisation loop is repeated as many times as the user wants to finally obtain a Pareto front.

Nevertheless, this framework is computationally unaffordable. For example, if 100 iterations are needed to find the Pareto, if the population is constituted of 20 individuals, if 15 parameters are considered uncertain for the uncertainty quantification and the PCE used is a second-order PCE, then the robust optimisation will take at least 393 days. This is due to the computational cost of the uncertainty quantification needed for each individual at each iteration. An uncertainty quantification with 15 uncertain parameters requires 68 model evaluations in this case. If each evaluation takes 250 sec, the uncertainty quantification of one individual will take 4.75 hours and this must be performed for each individual in every iteration. This simple example illustrates the curse of dimensionality that is often present when dealing with robust optimisation coupled to energy models, especially energy pathway models.

To circumvent this issue, the Simplified EnergyScope Pathway is replaced by another model which is computationally more affordable. The chosen approach is to use a surrogate model to approximate the Simplified EnergyScope Pathway model. As a reminder, a surrogate model is a function $\hat{f}$ that approximates the model response and has a much lower computational cost. For the sake of simplicity, the chosen surrogate model in the robust optimisation framework is the PCE since its implementation was already done for the uncertainty quantification. In practice, the surrogate model must approximate the output response depending on the decision variables $\boldsymbol{x}$ and the uncertainty parameters $\boldsymbol{\xi}$. The robust optimisation framework with this adaptation is illustrated in Figure 4.3.

Let's take an example to better understand this final version of the robust optimisation framework. Let's say that the purpose is to do a robust optimisation of the passenger mobility sector. The purpose is to identify which technologies in this sector can make the energy transition more robust. Therefore, the decision variables $\boldsymbol{x}$ of the multi-objective optimisation could be the installed capacity of those technologies during the transition. The uncertain parameters $\boldsymbol{\xi}$ relative to this sector could be the cost of those technologies and the cost of the resources used by those technologies. The purpose of the surrogate model will be to approximate the response of the model depending on those decision variables and those uncertain parameters. To do so, a PCE is used to approximate the total transition cost depending on the installed capacity of the passenger mobility technologies ($\boldsymbol{x}$) and on the uncertain parameters related to this sector ($\boldsymbol{\xi}$) :

$$\widehat{M}(\boldsymbol{\epsilon}) = \sum_{i=0}^{P} u_i \Psi_i(\boldsymbol{\epsilon}) \qquad\qquad \boldsymbol{\epsilon} = (\xi_1, ..., \xi_d, x_1, ..., x_n) \tag{4.2}$$

This PCE will be called the *Big PCE* in the rest of this master thesis to distinguish this PCE from the PCE that must be built for each individual to compute their mean and variance. When the Big PCE is built, it can replace the Simplified EnergyScope Pathway in the robust optimisation framework (see Fig. 4.3). Then, for each individual i, the Big PCE will be evaluated in q samples where the uncertain parameters $\boldsymbol{\xi}$ are

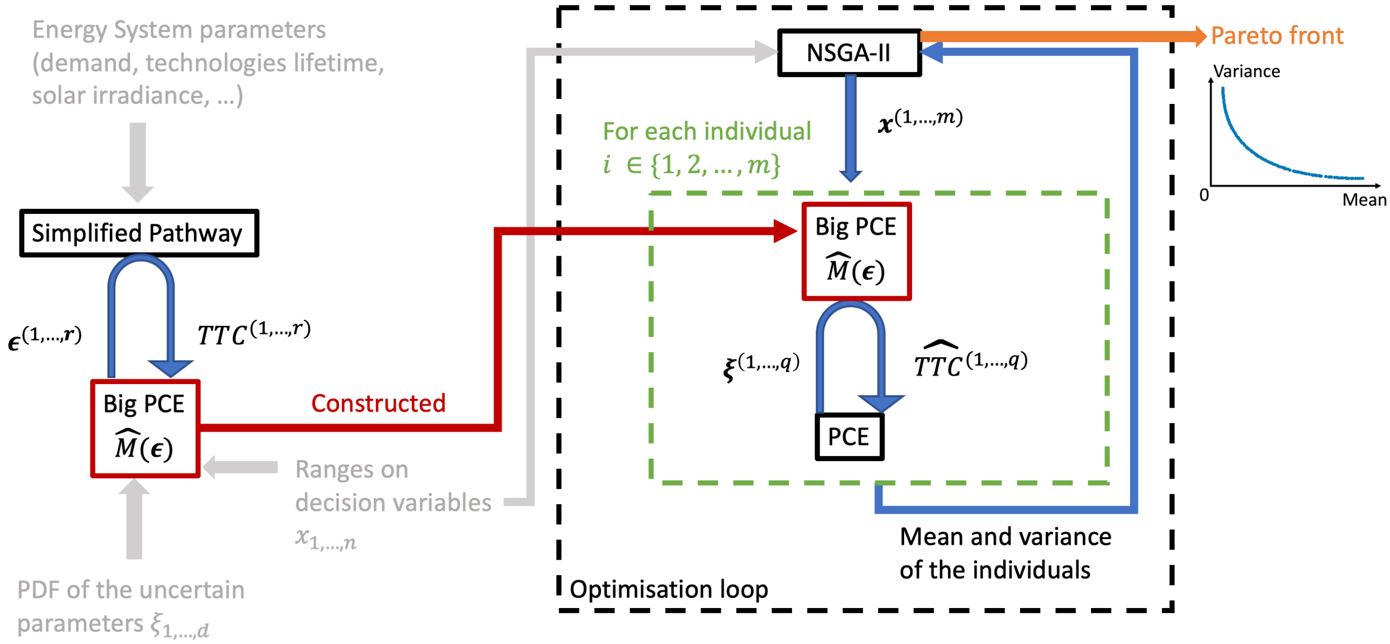

Figure 4.3: Final version of the robust optimisation framework. A polynomial chaos expansion (PCE), named Big PCE, is built to approximate the Simplified EnergyScope Pathway response depending on the uncertain parameters $\xi_{1,\dots,d}$ and the decision variables $x_{1,\dots,n}$. The Big PCE is then used, instead of the Simplified EnergyScope Pathway, in the optimisation loop. Then, the same steps as in the robust optimisation framework in Figure 4.2 are performed in order to build the Pareto front.

varied but the decision variables are fixed to the ones of the evaluated individual $\boldsymbol{x}^{(i)}$. Another PCE is then built based on those evaluations in order to compute the mean and variance of the total transition cost of the corresponding individual. This is done for each individual, a new population is created by NSGA-II and the process is reiterated. In the end, the Pareto front is built and the robust technologies are identified by analysing the decision variables of the points in the Pareto front.

Furthermore, the decision variables of the multi-objective optimisation must be defined. The best option that was found is that the decision variables are the maximum technologies capacity (f_{max}) that can be operational during the transition instead of the installed capacity (F) during each representative years. The installed capacity of a technology during the transition will be limited by this decision variables f_{max} with the following constraint in the model:

$$F(y,i) \leq f_{max}(i) \qquad y \in YEARS \backslash \{2020\},\ i \in TECHNOLOGIES \tag{4.3}$$

There are two reasons for this choice:

1. The maximum installed capacity were preferred over the installed capacity during the three representative years because three times less decision variables are needed for every technologie. More technologies can therefore be considered for a robust optimisation with this choice.

2. If the installed capacities during each representative year are the NSGA-II decision variables, then the coordinates of an individual could result in an unrealistic transition. As an example, if the installed capacity of wood boilers during each representative year are decision variables, then an individual could have a capacity of 0 GW in 2030, 40 GW in 2040 and 0 GW in 2050. Nothing guarantees that the 40 GW of wood boilers will be used. If they are not, then 40 GW of wood boilers will be installed

for nothing. Choosing the maximum installed capacity of technologies as decision variables gives more freedom to the model and does not constraint a technology to be installed for nothing.

Moreover, a methodology has been developed to identify which technologies are important to take as decision variables for the robust optimisation that will be performed in section 4.2. The methodology is fully described in Appendix D.3. The purpose of this methodology is to take as decision variables the technologies that impact the most the energy transition in order to perform a meaningful robust optimisation.

Furthermore, each decision variable (i.e. the maximum capacity of technologies) is limited by a certain range which is an approximation of the capacity required by this technology to supply the entire demand of its sector. For example, the maximum capacity of trucks is limited to 70 Mtkm/h, which is the approximated capacity required by one type of truck to supply the truck share of the freight mobility demand during a year (see the methodology described in Appendix D.3).

Finally, the purpose of a robust optimisation is to identify what technologies must be installed to decrease the variation of the energy transition cost due to uncertainties. Therefore, when performing an uncertainty quantification of an individual, the transition strategy should not change much between two model evaluations. The same technologies must be used in every model evaluations to simulate a real-life situation, where we install technologies and we don't know how the parameters will vary from their nominal value but we want to minimise the variation of the energy transition in any case. To ensure it, the decision variables are also constrained by NSGA-II to force a little the technologies that will be used in the transition. The decision variables of a same category (e.g. boilers, cars, buses, trucks, ...) are constrained to limit the sum of their capacity to that individual limit. Let's take the example of the trucks: the maximum capacity of every type of truck is limited to 70 Mtkm/h (see appendix D.3). Therefore, a NSGA-II constraint forces the sum of the maximum capacity of trucks to be smaller than or equal to 70 Mtkm/h. With this constraint, the trucks that can be used during the transition are limited. Otherwise, if an individual has its maximum capacity of trucks all equal to 70 Mtkm/h, then different model evaluations for this individual could result in different transition strategies where different trucks are used.

4.2 Results

This section analyses the results obtained from robust optimisations with the robust optimisation framework explained above. This section also illustrates the difficult trade-off between the robust optimisation accuracy and the computational time when performing a robust optimisation with an energy pathway model. First, a simple case will be presented as an illustrative example to better understand the robust optimisation framework and the following results. Then, two robust optimisations will be performed on the overall energy system in order to analyse what technologies improve the robustness of the energy transition. The difference between the two robust optimisations is that one will use a sparse Big PCE and the other one a full Big PCE to compare the two.

4.2.1 Simple case

In this case, only the uncertainty on renewable energy are taken into account and the decision variables are the maximum capacity of photovoltaic (PV) panels, onshore wind turbines and offshore wind turbines. Table 4.1 resumes the uncertain parameters and the decision variables of this case.

The Pareto front of the mean and variance of the total transition cost for this robust optimisation problem is shown in Figure 4.4. This Pareto front is coherent since the energy transition that minimises the standard deviation is an energy transition without PV panels and without wind turbines since they are strongly impacted by the uncertainties. On the other hand, the energy transition that minimises the mean is a

Table 4.1: Uncertain parameters and decision variables of the simple robust optimisation problem performed in this sub-section.

Name	Description	Range
	Uncertain parameters ξ_i	
cpt_ren	hourly availability of solar and wind energy	[−11.1% ; 11.1%]
c_inv_PV	Price of photovoltaic (PV) panels	[−39.6% ; 39.6%]
c_inv_wind	Price of onshore and offshore wind turbines	[−21.6% ; 22.9%]
	Decision variables x_i	
$f_{max}(PV)$	maximum capacity of PV panels	[0GW ; 59.175GW]
$f_{max}(WIND\_ONSHORE)$	maximum capacity of onshore wind turbines	[0GW ; 10GW]
$f_{max}(WIND\_OFFSHORE)$	maximum capacity of offshore wind turbines	[0GW ; 3.5GW]

transition where the full potential of PV panels and wind turbines can be installed. It is in accordance with the analysis of the different deterministic scenarios, in section 2.2 and 2.3, where PV panels and wind turbines are used up to their full potential in every scenario.

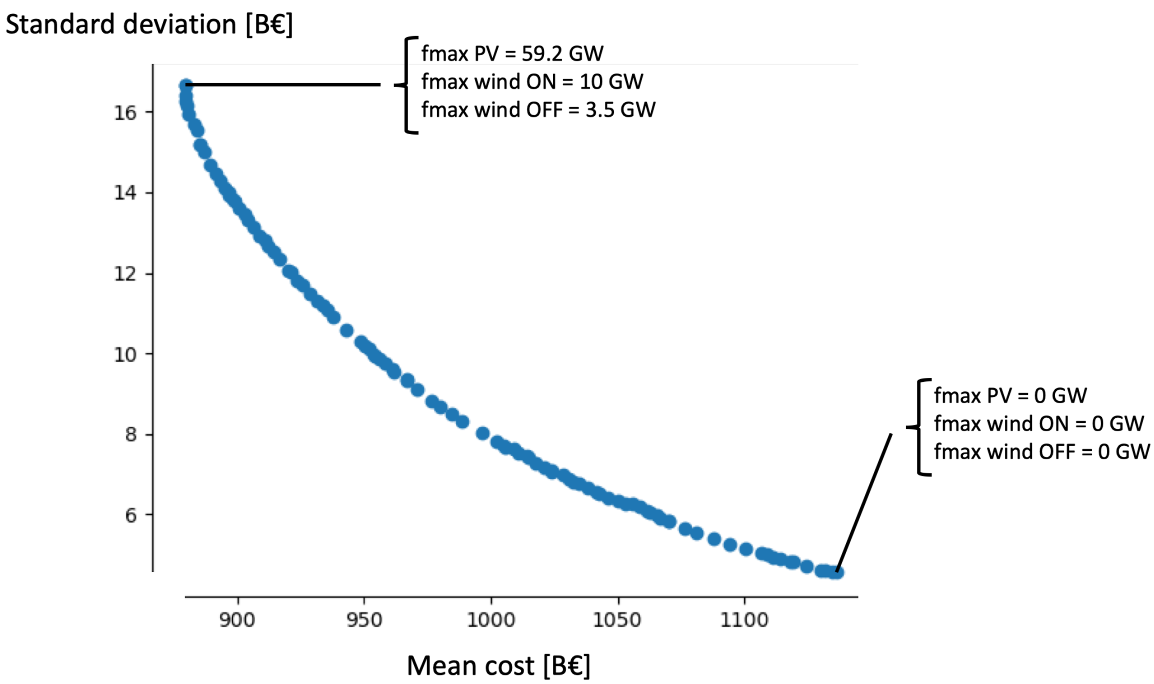

Figure 4.4: Pareto front of the robust optimisation problem, resumed in Table 4.1, where the mean and standard deviation of the total transition cost are the objectives to minimise. Not using photovoltaic (PV) panels and wind turbines minimises the standard deviation as the only uncertainties are on renewable energy. However, to minimise the mean, the maximum capacity of those technologies is their potential in Belgium.

4.2.2 Robust optimisation on the overall Belgium energy transition

The purpose of this section is to identify which technologies improve the robustness of the energy transition in Belgium. The purpose is also to compare the use of a sparse Big PCE and a full Big PCE.

The uncertain parameters ξ_i, for this robust optimisation, are resumed in Appendix D.1 and represent the resources price and availability, the technologies price, the end-use demands, the technologies efficiency and the hourly availability of solar and wind energy. The decision variables x_i, of the robust optimisation, are the maximum capacity of technologies obtained from the methodology described in Appendix D.3. Those decision variables are resumed in Table D.2 of this Appendix. Furthermore, some storage technologies were removed from the Simplified EnergyScope Pathway to decrease its computational cost. This is explained in Appendix D.2.

Based on those uncertain parameters and decision variables, two robust optimisations were performed : one where the Big PCE is a full PCE and one where it is a 50% sparse PCE. The 50% sparse Big PCE is built with the same decision variables as the full Big PCE but NSGA-II will only modify the decision variables x_i that have a non-zero polynomial in the Big PCE as only those variables will influence the output. In other words, if none of the multivariate polynomials Ψ_j depending on a variable x_i is part of the sparse Big PCE, then this variable x_i will not be a part of the robust optimisation since changing its value will have no influence on the total transition cost approximated by the sparse Big PCE.

First, let's analyse the accuracy of the full and the 50% sparse Big PCE to predict the Simplified EnergyScope Pathway output. Two methods were used to assess their accuracy. The first method is the LOO error described in section 3.2.3. As a rule of thumb, a PCE predicts accurately the Simplified EnergyScope Pathway output if its LOO error is below 0.01. The LOO error of the full and the 50% sparse PCE is respectively 0.013 and 0.012. Consequently, the two Big PCE does not respect the rule of thumb. However, as explained in section 3.3.1, there is a trade-off between the accuracy of the PCE and the computational time. Improving the accuracy of the PCE would result in a drastic increase of the computational time which is not affordable.
In this case, the Big PCE is of order 2 and is constituted of 54 parameters (19 uncertain parameters and 35 decision variables). The number of model evaluations to build a full PCE is therefore 3080 with equation 3.20. Taking a mean time of 250 seconds for one evaluation of the Simplified EnergyScope Pathway model, the time required to evaluate 3080 samples will be 9 days. In order to improve the accuracy of the PCE, and therefore decrease the LOO error, a PCE of order 3 instead of 2 could be used. In that case, 58520 model evaluations will be required which results in a computational time of 171 days. This is unaffordable. Moreover, with a third-order PCE and a computational time limit of 9 days, the number of parameters that would be allowed is 19. This illustrates the trade-off between the computational time, the Big PCE accuracy and the number of parameters (uncertain parameters + decision variables) that can be taken into account.

The second method to assess the accuracy of the two Big PCEs is the comparison of the Big PCE output to the Simplified EnergyScope Pathway output in random samples. 1000 random samples of the uncertain parameters and the decision variables were evaluated by the Simplified EnergyScope Pathway model and the Big PCEs in order to compare the total transition cost of those two models. The histograms of the error made by the full and the 50% sparse Big PCE are presented in Figure 4.5. To assess the accuracy of the two Big PCE, the root mean square of the error is computed. The root mean square of the errors are respectively 1.36 and 1.28 for the 50% sparse and the full Big PCE. Even root mean square below 1% would have been preferred, those two Big PCEs are deemed accurate enough because of the trade-off illustrated above.

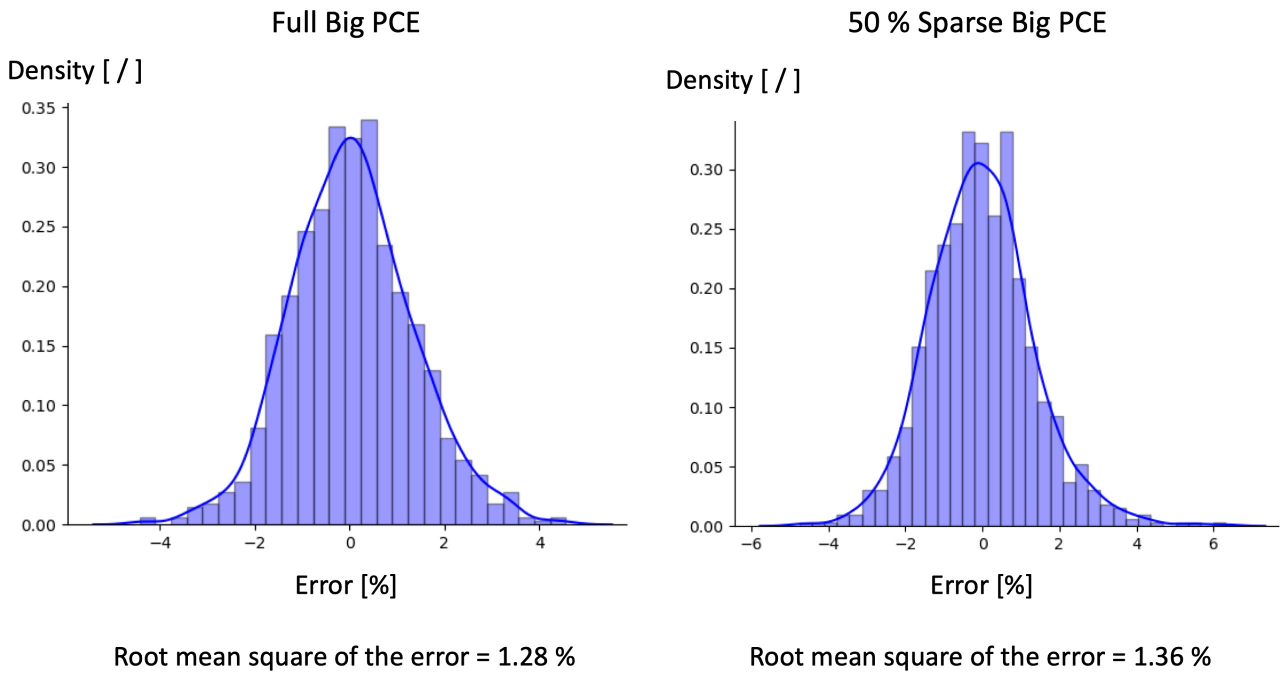

Figure 4.5: Histogram and Kernel smoothing of the error made by a full and 50% sparse Big PCE on 1000 random samples compared to the Simplified EnergyScope Pathway model. The root mean square of the Big PCE error is also written. The Full Big PCE approximates more accurately the Simplified EnergyScope Pathway output as the range of the error and the root mean square of the error are smaller than with a 50% sparse Big PCE.

The Pareto fronts resulting from the robust optimisation problem are presented in Figure 4.6 and Figure 4.7 with a 50% sparse Big PCE and a full Big PCE respectively. The real points are also present for the two extreme points of the Pareto front. Real points are obtained by performing an uncertainty quantification on the Simplified EnergyScope Pathway model with the decision variables of the corresponding point.

Concerning the use of a 50% sparse Big PCE, the Pareto front is unfortunately not accurate (see Fig. 4.6). Indeed, the real points are far from their corresponding point in the Pareto. Moreover, one of the two real points dominates the other as it has a lower mean and standard deviation. This means that building a Pareto front using a sparse PCE does not give correct results. A sparse Big PCE is therefore inappropriate for the Big PCE of the robust optimisation framework.

Concerning the use of a full Big PCE, the Pareto front is better (see Fig. 4.7). The real points are a Pareto front since neither of the two dominates the other. Nevertheless, those two points are closer than expected. The difference between the two is very small (0.3% for the mean and 0.6% for the standard deviation). Therefore, the gain of robustness between the less and most robust point is small.

Between those two points, six decision variables are varying significantly. The variation of those decision variables is presented in Figure 4.8. Based on those results:

- H_2 trucks and NG buses are more robust than electric trucks and diesel buses, respectively, as they decrease the standard deviation of the total transition cost.

- Diesel boat adds robustness to the energy transition. The rest of the boat share is supplied by NG boat.

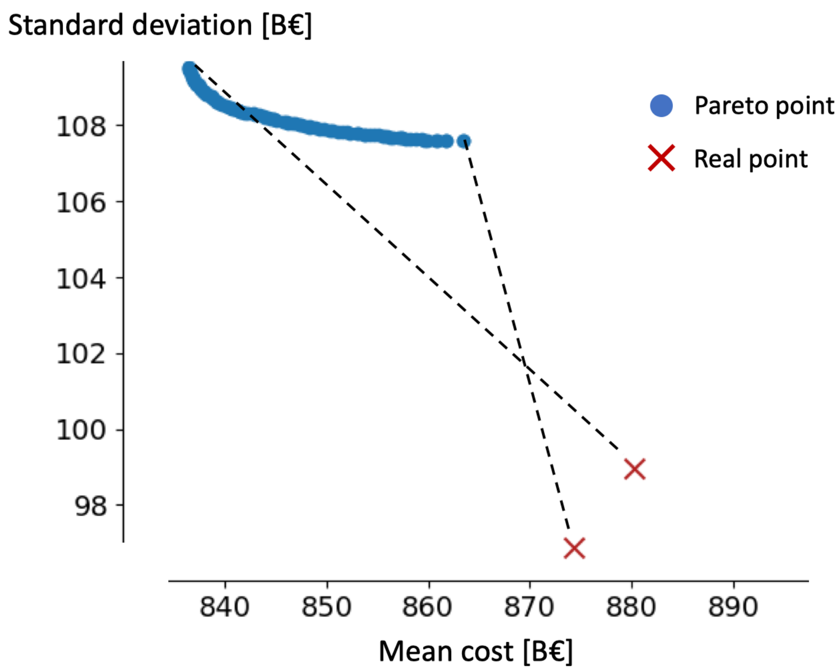

Figure 4.6: Pareto front of the mean and standard deviation of the total transition cost with a 50% sparse Big PCE. For the extreme points of this Pareto front, the real mean and standard deviation with the corresponding decision variables were computed with an uncertainty quantification on the Simplified EnergyScope Pathway (red crosses). The Pareto front is not accurate since the two real points are not a Pareto.

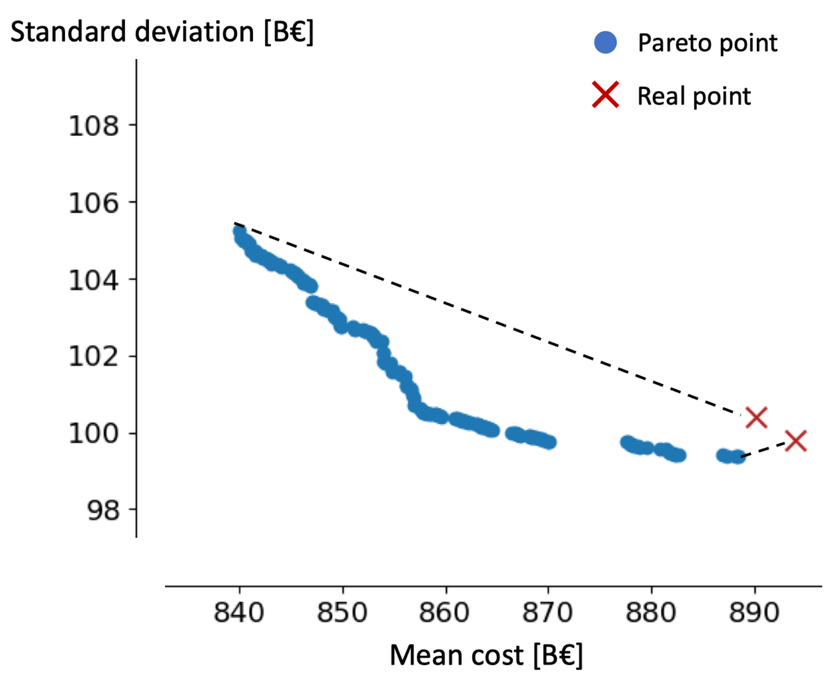

Figure 4.7: Pareto front of the mean and standard deviation of the total transition cost with a full Big PCE. For the extreme points of this Pareto front, the real mean and standard deviation with the corresponding decision variables were computed with an uncertainty quantification on the Simplified EnergyScope Pathway (red crosses). The Pareto front is tighter in reality but the real points are a Pareto.

Nevertheless, it is important to remember that the two real points are close to each other. The 99% confidence interval of the total transition cost only decreases by 0.6% between the point with the minimum variance and the point with the maximum variance (514 B€ and 517 B€). Therefore, H_2 trucks, NG buses and diesel boats are in fact only slightly more robust than electric trucks, diesel buses and NG boat.

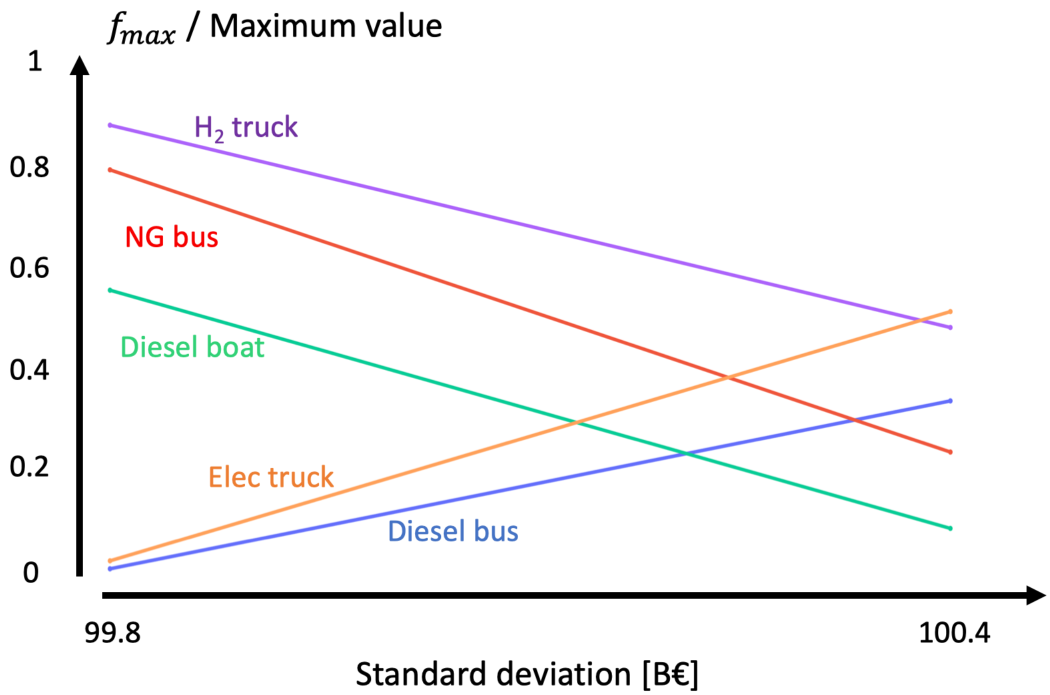

Figure 4.8: Ratio between the f_{max} and its maximum value for the technologies with a variation bigger than 30% between the two real points of Figure 4.7. For example, the real point with a standard deviation of 99.8 B€ has a $f_{max}(\mathrm{H_2\,truck}) = 61.7 = 0.88 \cdot 70$ Mtkm/h with 70 Mtkm/h the limit of $f_{max}(\mathrm{H_2\,truck})$. H_2 truck, NG bus and diesel boat add robustness to the energy transition.

In conclusion, the robust optimisation framework reaches partially its purpose but only when using a full Big PCE. The robust optimisation framework manages the curse of dimensionality and identifies some robust technologies. However, in the results presented above, the real Pareto front is tight as the more robust and the less robust point are close to each other. It means that the robust optimisation framework did not find an energy transition strategy that is significantly more robust than others. Moreover, only three robust technologies were identified. This is not much, but the robust optimisation framework can still be improved and has interesting potential to identify more robust technologies, as discussed in the next chapter.

Discussion

This section discusses the validity of this master thesis results and provides areas for improvements that could be assessed in future works.

Data for the Belgium energy transition

First of all, all the data used for the EnergyScope Pathway input parameters come from the PhD thesis of Gauthier Limpens [6]. He provides a complete database, based on multiple works in the literature, for the parameters required to represent the Belgium energy transition. However, the data are always subject to improvement if better sources are found. This is why Gauthier Limpens fully describes the sources he used. This allows for future works to improve those data with more recent data. The only data used in this master thesis that are not in the PhD thesis of Gauthier Limpens are the data representing the Belgium energy system in 2020. To complement the great database of Gauthier Limpens, those data are provided in Appendix A with the sources used for each data.

Nevertheless, the data on synthetic fuels and biofuels must be taken with caution. It was assumed that the CO_2 emissions related to the use of these fuels are negligible. However, more data should be researched to assess a precise value of the CO_2 emissions related to the consumption of those fuels. This could change the outcome of the Belgium energy transition since synthetic fuels are massively used towards the end of the transition because their use is assumed to be carbon neutral. Moreover, the unlimited availability of these fuels in the EnergyScope Pathway model is also subject to discussion. If every country transits towards a sustainable energy system and starts using synthetic fuels, then synthetic fuels to import could become scarce. Or maybe they would come from the other end of the world and the CO_2 emissions related to this transport would be important.

Therefore, there is a need to search for accurate data on the related CO_2 emissions and the availability of synthetic fuels and biofuels in order to model an energy transition with even more realism. This matter will probably be assessed in the upcoming PhD thesis of Xavier Rixhon about the role of RE-fuels in the Belgium energy transition.

However, the transition scenarios analysed in this master thesis are still meaningful. They prove that fossil fuels must be substituted and that, in Belgium, there is not enough renewable energy to supply the energy demand. Belgium needs to use new resources that are carbon-neutral and electrify the system to fully use renewable energy, as explained in this master thesis.

Only the CO_2 emissions of resources are limited

The CO_2 emissions related to the technologies construction and installation were not taken into account for the CO_2 limit to respect. It is worth mentioning that if they are, the model does not find an energy transition, for Belgium, that respects the CO_2 emissions limit. It shows the need to decrease the CO_2 emissions related to the technologies construction and installation by using more eco-responsible method or by extending the lifetime of technologies. Another solution could also be to use carbon capture and storage technologies to reduce the CO_2 balance. Those technologies were not taken into account in this master thesis but it will be interesting to analyse how they could help the Belgium energy transition.

Data uncertainty

The used data are uncertain and this uncertainty must be taken into account, as they were in this master thesis. The data used for the uncertainties on input parameters were obtained with a rigorous method from the PhD thesis of S. Moret [7]. However, the uncertainty of a parameter can always be decreased by acquiring more knowledge on this parameter. Moreover, the probability density function (PDF) used to describe the uncertainties was always a uniform distribution because of data scarcity. It is likely that some parameters follow another distribution which will change the uncertainty of this parameter. Having more knowledge on the range and PDF of the uncertain parameters will decrease the uncertainty on the Belgium energy transition and make an uncertainty analysis more meaningful.

Robust optimisation with energy pathway models

Concerning the robust optimisation of an energy pathway model, the developed robust optimisation framework, described in section 4.1, proved that robust optimisation and energy pathway models can be compatible with some simplifications. This could be promising for future works, as robust optimisation with energy pathway models is still a rare and feared topic. Moreover, the robust optimisation framework considers the model as a black box, which makes it easy to use with other energy pathway models.

Furthermore, the robust optimisation framework has room for improvement. The NSGA-II constraints to perform a more realistic robust optimisation can be improved for the low temperature heat sector. Indeed, the heat pumps were not constrained with the other technologies of the low temperature heat sector. It means that different strategies could be chosen for a single individual. Interestingly, the sector where robust technologies were identified is the mobility sector, which is the sector where constraints are best implemented. Therefore, improving the constraint on the low temperature heat technologies might help to identify the robust technologies in this sector as well.

The EnergyScope Pathway is meant for great works

Analysing relevantly different transition scenarios was only possible because of the great features that possesses the EnergyScope Pathway model. This model succeeds in modelling a pertinent energy transition in a reasonable time. This model is also open-source and can therefore be used to model any country or region if the input parameters required are known.

Moreover, performing an uncertainty analysis and a robust optimisation was made possible thanks to the Simplified EnergyScope Pathway model, developed and described in this master thesis. This model allows uncertainties to be taken into account in a meaningful way and in a reasonable time. This can encourage other countries to use this energy pathway model which will help them plan effectively their energy transition and identify the most important areas where uncertainties must be decreased.

To conclude this discussion, this master thesis tried to be as complete as possible, but it is only the tip of the iceberg of what could be done with the EnergyScope Pathway model and its simplified version. More scenarios could be analysed or more technologies could be implemented. Those model could also be extended into a multi-regional energy system to analyse how different countries could transit together towards energy sustainability, as it was done for EnergyScope TD in the master thesis of P. Thiran et al. [40].

Conclusion

This master thesis analysed what is the optimal pathway towards energy sustainability in Belgium, using a novel energy pathway model developed by Gauthier limpens and called EnergyScope Pathway [6]. Whatever the context, the optimal pathway for Belgium was always following four keys to transit towards energy sustainability by 2050 : 1) More efficient technologies are installed during the transition. 2) Fossil fuels are substituted by renewable energy, imported electricity and synthetic fuels to mitigate CO_2 emissions. 3) The energy system is electrified to fully use the electricity production from renewable energy. 4) Storage technologies are used to manage the intermittency of renewable energy.

Moreover, different transition contexts were analysed to understand how those contexts could impact the Belgium energy transition:

> **What if nuclear power is not phased-out ?** If nuclear power plants are not phased out, they could be a real asset for the Belgium energy transition. The nuclear power plants could produce 44 TWh/year of electricity and allow Belgium to deploy renewable energies more slowly. The cost of the transition will be smaller as nuclear energy is cheap to produce and the nuclear power plants are already paid for. In the end, nuclear power plants are compatible with a sustainable energy system because few CO_2 emissions are related to the consumption of uranium.
>
> **What if Belgium can not import electricity ?** Another scenario was analysed where Belgium would not import electricity, in case neighbouring countries transit towards energy sustainability with us and will want to import electricity when Belgium will. In this case, the optimal way to adapt is by installing more industrial gas CHPs and more CCGTs. Those power plants will have to use synthetic natural gas at the end of the transition to respect the CO_2 emissions limit.
>
> **What budget could be set by politicians ?** This is intended for politicians to present and give an order of magnitude for a constant 5-year budget to invest in new technologies. The optimal constant budget to set would be 95.15 B€. Of course, not every investment is taken into account in this budget (e.g. electric and hydrogen stations are not) but this gives an idea of the budget that could be set.

Furthermore, uncertainties needed to be taken into account to have the global picture on the Belgium energy transition, but uncertainty analysis and global sensitivity analysis are still limited in the energy field. To solve this, this master thesis proposed to use a polynomial chaos expansion (PCE) method that can perform an uncertainty analysis and a global sensitivity analysis. However, the curse of dimensionality was still limiting the uncertainty analysis. Therefore, a stepwise regression method to build a sparse PCE is used to decrease the computational time. After analysing this method with the energy model EnergyScope TD, this stepwise regression method can reduce the computational time by 60%, or even 80% if an error of 2% is allowed.

Moreover, a simplified version of the EnergyScope Pathway model was developed to perform an uncertainty analysis in an affordable time. This simplified version, called Simplified EnergyScope Pathway, accurately approximates the EnergyScope Pathway and is five times faster. This model opens the door for uncertainty analysis and robust optimisation of an energy transition.

By coupling the Simplified EnergyScope Pathway and a sparse PCE method, an uncertainty analysis and a global sensitivity analysis were performed on the overall Belgium energy transition, taking into account uncertainties on the resources price and availability, the technologies price, the renewable potential, the end-use demands (EUDs), the technologies efficiency and the availability of solar and wind. Therefore, this master thesis proved that analysing uncertainties with an energy pathway model is affordable with a sparse PCE and with the Simplified EnergyScope Pathway model that will be open-source.

Firstly, the uncertainty analysis showed that the uncertainty on the Belgium energy transition cost will increase during the transition as new technologies and new resources are used but are more uncertain than fossil fuels and old technologies used today. Secondly, the global sensitivity analysis identified the parameters that are most responsible for the uncertainty on the Belgium transition cost. During the beginning of the transition, the uncertainties on fossil fuels and on old technologies are the most responsible but, as time goes by, synthetic fuels and new technologies, especially new transport technologies (e.g. fuel-cell vehicle, electric car, ...), becomes the major driver of the Belgium transition cost uncertainty. Therefore, the priority to decrease the uncertainty on the Belgium energy transition cost is to acquire more knowledge on new transport technologies (e.g. hydrogen transports, electric transports, ...) and reduce the uncertainty on the price of fossil fuels and synthetic fuels.

Finally, in order to plan a robust energy transition (i.e. a transition that is little influence by uncertainties), a robust optimisation of the Belgium energy transition is required. The issue was that applications of robust optimisations with energy pathway models are still limited because of the high computational time usually required. In this master thesis, a novel robust optimisation framework was presented to perform a meaningful robust optimisation in an affordable time. This robust optimisation framework can be used to identify the technologies that can make the energy transition more robust, which will help to plan a robust pathway towards energy sustainability.

This framework was used to perform a robust optimisation on the overall Belgium energy transition to identify which technologies can make the transition more robust. The robust optimisation framework did not found a path much more robust than others, but it still identified that hydrogen trucks, natural gas buses and diesel boats are slightly more robust than electric trucks, diesel buses and natural gas boats for the Belgium energy transition.

Moreover, this robust optimisation framework can be improved, as discussed in the previous chapter. This framework might have the potential to find more robust technologies and be a real tool for helping planning a robust energy transition towards energy sustainability.

Appendices

Appendix A

Belgium energy system in 2015 and 2020

This appendix contains the used value to fix the 2015 and 2020 Belgium energy system in the EnergyScope Pathway model presented in section 1.2. Data for the year 2015 come from the PhD thesis of Gauthier Limpens [6]. Data for 2020 come from multiple sources which are referenced in the following tables. Since this master thesis is realised in 2021, the available data of the 2020 Belgium energy system are scarce. Consequently, the most recent sources were used in order to approximate the 2020 Belgium energy system.

Table A.1: Capacity [GW] and electricity shares [%] of electric sector technologies in Belgium. Abbreviations : combined cycle gas turbine (CCGT).

Technology	**Capacity [GW] in 2015**	**Capacity [GW] in 2020**	**Electricity shares[a] [%] in 2020**
photovoltaic	3.85	4.65[b]	3.5 - 4.2
onshore wind	1.18	2.3[c]	3.4 - 4
offshore wind	0.69	1.55[c]	4.6 - 5.5
hydro river	0.11	0.11[d]	-
geothermal	0.0	0.0[d]	-
nuclear power plant	5.925	5.925	41.4 - 48.8
CCGT	3.925	3.925[e]	-

[a]Assumed similar to the shares in 2019. Data comes from a press release from Elia [14].
[b]mean between the value in [41] and at `https://www.febeg.be/fr/statistiques-electricite` for 2019
[c]from [42,43] for 2019.
[d]Same as 2015 since no improvement was foreseen as explained in [6].
[e]No data was found on new CCGT installations between 2015 and 2020.

Table A.2: Yearly shares of multiple sub-sectors. Abbreviations : district heating network (DHN).

	2015	**2020**
$\%_{public}$	19.9%	19.4% [44]
$\%_{Freight,rail}$	10.9%	10.2% [44]
$\%_{Freight,boat}$	15.6%	16.0% [44]
$\%_{DHN}$	2.0%	2.0%[a]

[a]Because of the lack of data for this parameter, the same value as 2015 has been taken.

Table A.3: Yearly shares of private mobility for the Belgium energy system. Data for the year 2020 come from [45]. Abbreviations : natural gas (NG), hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV), fuel cell (FC).

	2015	**2020**
Diesel car	63.7%	51.0%
Gasoline car	35.3%	48.5%
NG car	1.0%	0.2%
HEV	0.0%	0.0%
PHEV	0.0%	0.0%
BEV	0.0%	0.3%
FC car	0.0%	0.0%

Table A.4: Yearly shares of public mobility for the Belgium energy system. Data for the year 2020 come from [44]. The repartition between the types of buses in 2020 is assumed similar to 2015 because of the lack of data. Abbreviations : natural gas (NG), fuel cell (FC).

	2015	**2020**
Diesel bus and coach	47.0%	43.0%
Diesel hybrid bus and coach	0.0%	0.0%
NG bus and coach	10.0%	9.0%
FC bus and coach	0.0%	0.0%
Train / metro	38.5%	43%
Tram and trolley bus	4.5%	5%

Table A.5: Yearly shares of decentralised low temperature heat and CHP technologies for the Belgium energy system. Data for 2020 are assumed similar to 2015 because of the lack of data. Abbreviations : liquid fuel oil (LFO), natural gas (NG), cogeneration of heat and power (CHP), electric heat pump (eHP), thermal heat pump (thHP).

	2015	**2020**
Boiler LFO	48.4%	48.4%
Boiler NG	39.6%	39.6%
Boiler wood	10.0%	10.0%
CHP NG	0.7%	0.7%
CHP LFO	0.0%	0.0%
eHP	1.1%	1.1%
thHP	0.0%	0.0%
Solar thermal	0.2%	0.2%
Electric heater	0.0%	0.0%

Table A.6: Yearly shares of DHN low temperature heat and CHP technologies for the Belgium energy system. Data for 2020 are assumed similar to 2015 because of the lack of data. Abbreviations : cogeneration of heat and power (CHP), natural gas (NG), liquid fuel oil (LFO), electric heat pump (eHP).

	2015	**2020**
CHP NG	59.4%	59.4%
CHP wood	6.6%	6.6%
CHP waste	14.1%	14.1%
Boiler NG	13.9%	13.9%
Boiler LFO	0.7%	0.7%
Boiler wood	0.0%	0.0%
eHP	4.4%	4.4%
Deep geothermal	1%	1%

Table A.7: Yearly shares of industrial high temperature heat and CHP technologies for the Belgium energy system. Data for 2020 are assumed similar to 2015 because of the lack of data. Abbreviations : natural gas (NG), liquid fuel oil (LFO), cogeneration of heat and power (CHP).

	2015	**2020**
Boiler NG	35.8%	35.8%
Boiler coal	30.0%	30.0%
Boiler LFO	20.0%	20.0%
Boiler wood	0.0%	0.0%
Boiler waste	0.0%	0.0%
CHP NG	8.6%	8.6%
CHP wood	0.0%	0.0%
CHP waste	5.6%	5.6%
Industrial electric heater	0.0%	0.0%

Appendix B

EnergyScope Pathway vs Simplified EnergyScope Pathway

For the analysis of the different scenarios analysed in the previous sections, the EnergyScope Pathway model was used. However, as explained in section 1.3, a faster model is needed in order to perform an uncertainty analysis and a robust optimisation on the Belgium energy transition. Therefore, the Simplified EnergyScope Pathway was developed and is described in section 1.3. This model optimises the Belgium energy transition 5 times faster than the EnergyScope Pathway model by modelling 4 representative years instead of 8.

Two criteria must be met for the Simplified EnergyScope Pathway to be an accurate approximation of the EnergyScope Pathway : the error on the total transition cost must be below 1% and the overall strategy of the transition must be similar (i.e. what technologies must be installed and when, what resources is used and when, ...).

For the first criteria, the total transition cost of the two models was compared in the four scenarios analysed in the previous section. The error is 0.12% for the basic scenario, 0.65% for the nuclear scenario, 0.16% for the zero imported electricity scenario and 0.25% for the phase budget scenario. Consequently, the error of the Simplified EnergyScope Pathway on the total transition cost is indeed below 1%.

For the second criteria, the used resources and the transition in each energy sectors, for the basic scenario, are compared in Figure B.1 to Figure B.6. Those figures prove that the overall strategy is similar between the two pathway models. The same resources are used to substitute fossil fuels and the same technologies are used, at approximatively the same time, to transit towards sustainability in every energy sectors.

In conclusion, the Simplified EnergyScope Pathway is an accurate approximation of the EnergyScope Pathway and can therefore be used for an uncertainty quantification and a robust optimisation on the Belgium energy transition.

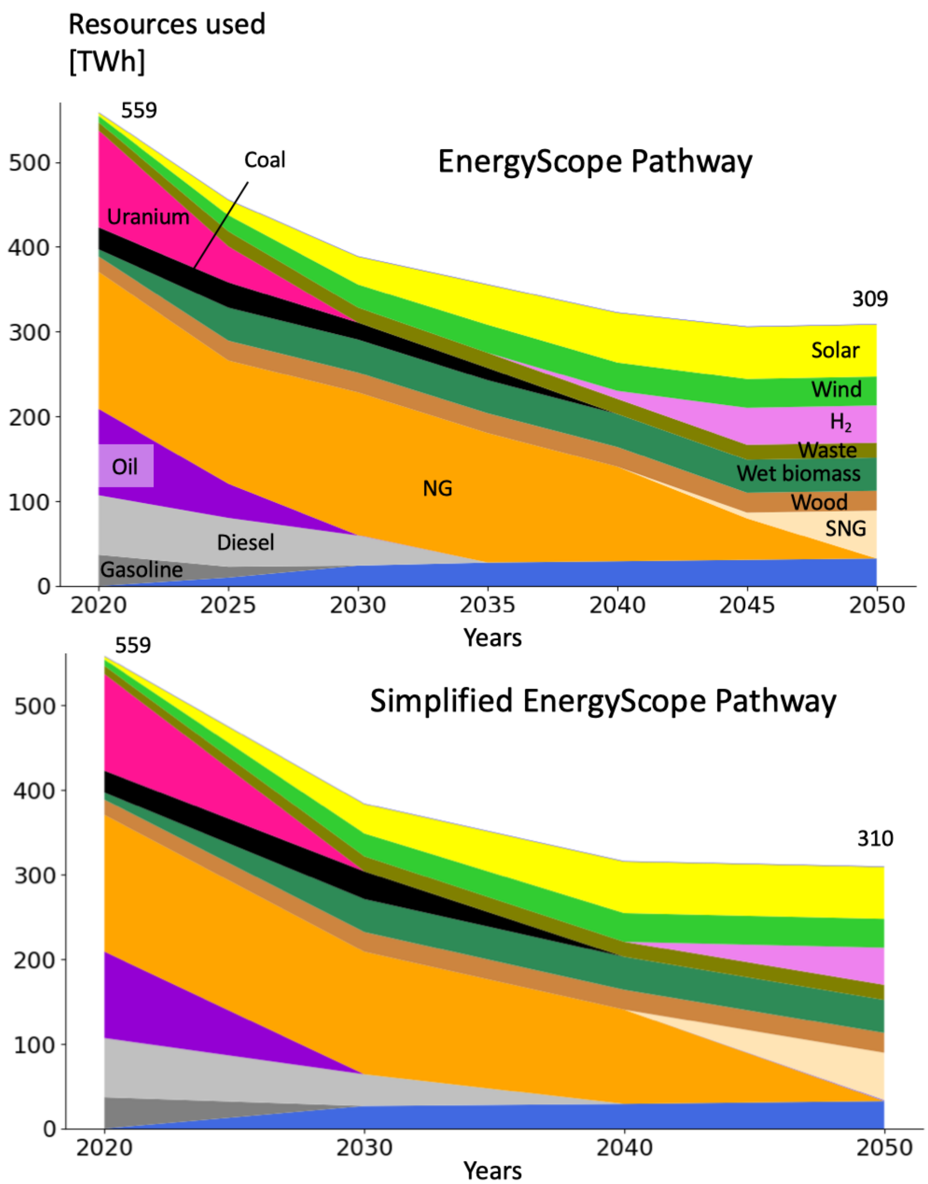

Figure B.1: Resources used in the Belgium energy transition with the EnergyScope Pathway and the Simplified EnergyScope Pathway model. The two transitions are similar from a resources point of view as fossil fuels are substituted by the same resources. Abbreviations : natural gas (NG), hydrogen (H_2), synthetic natural gas (SNG).

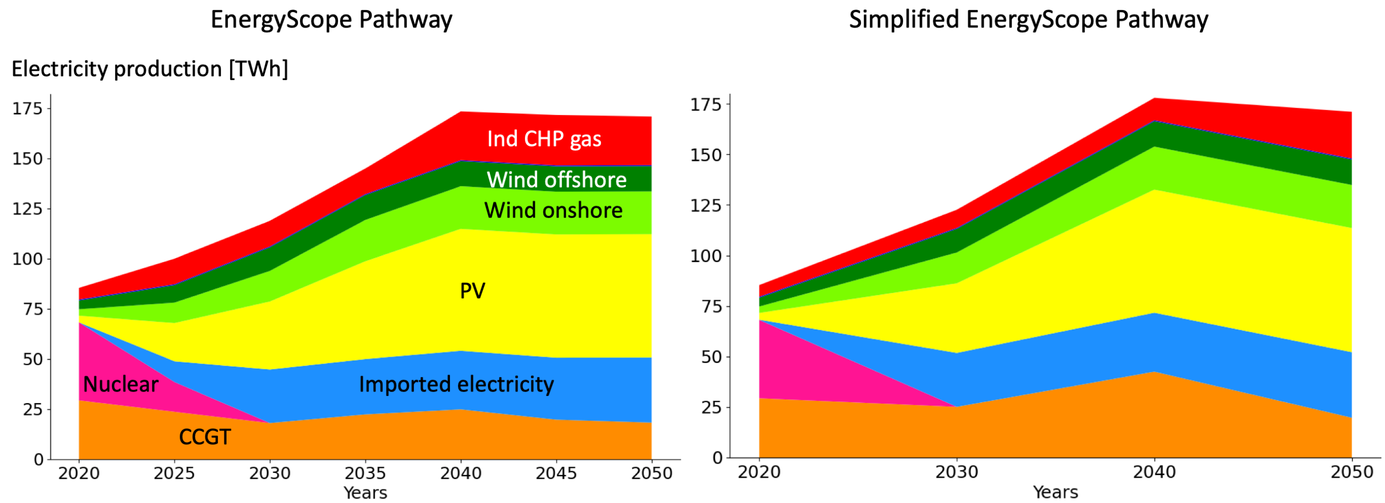

Figure B.2: Electricity produced during the transition with both models. Abbreviations : district heating network (DHN), photovoltaic (PV), combined cycle gas turbine (CCGT), industrial gas co-generation power plants (Ind cogen gas).

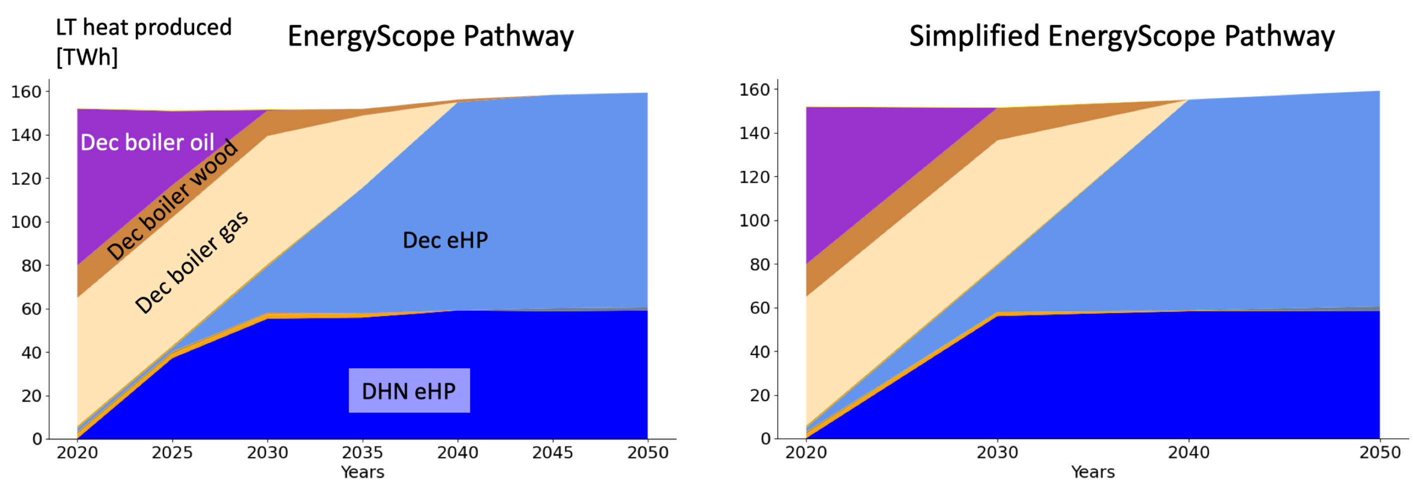

Figure B.3: Low temperature (LT) heat produced during the transition with both models. Abbreviations : district heating network (DHN), decentralised (Dec), electric heat pump (eHP).

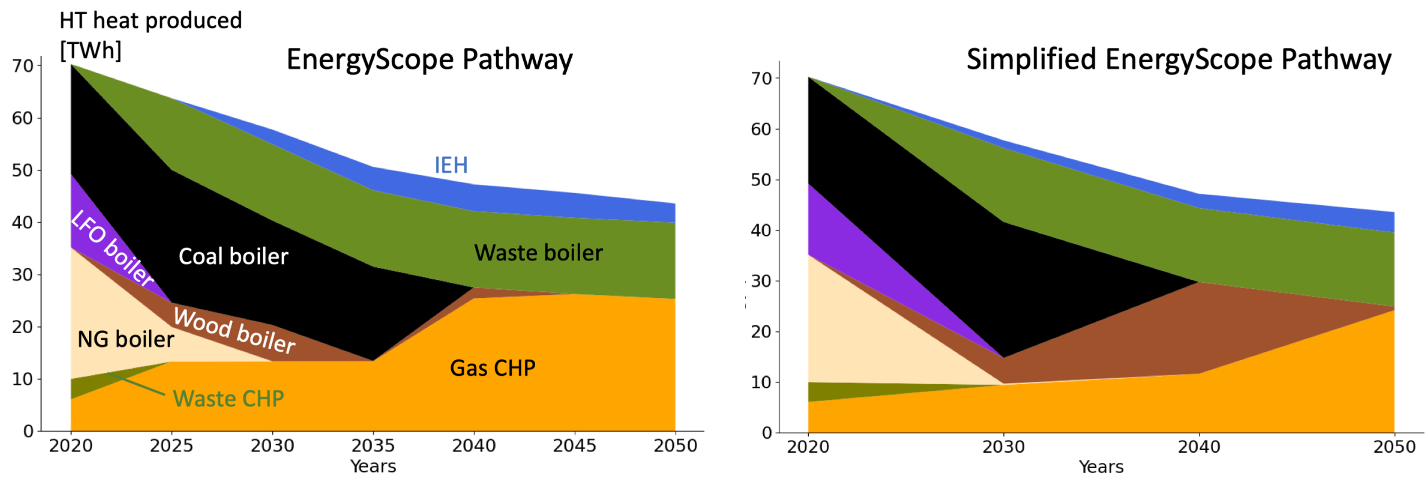

Figure B.4: High temperature (HT) heat produced during the transition with both models. Abbreviations : natural gas (NG), cogeneration of heat and power (CHP).

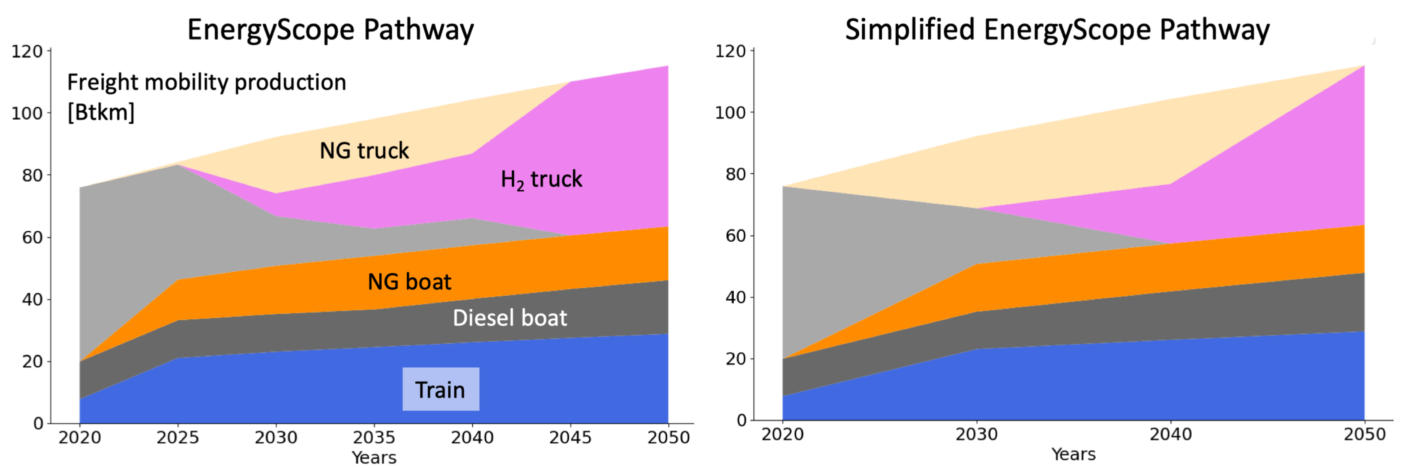

Figure B.5: Freight mobility production during the transition with both models. Abbreviations : billions ton-kilometer (Btkm), natural gas (NG), hydrogen (H_2).

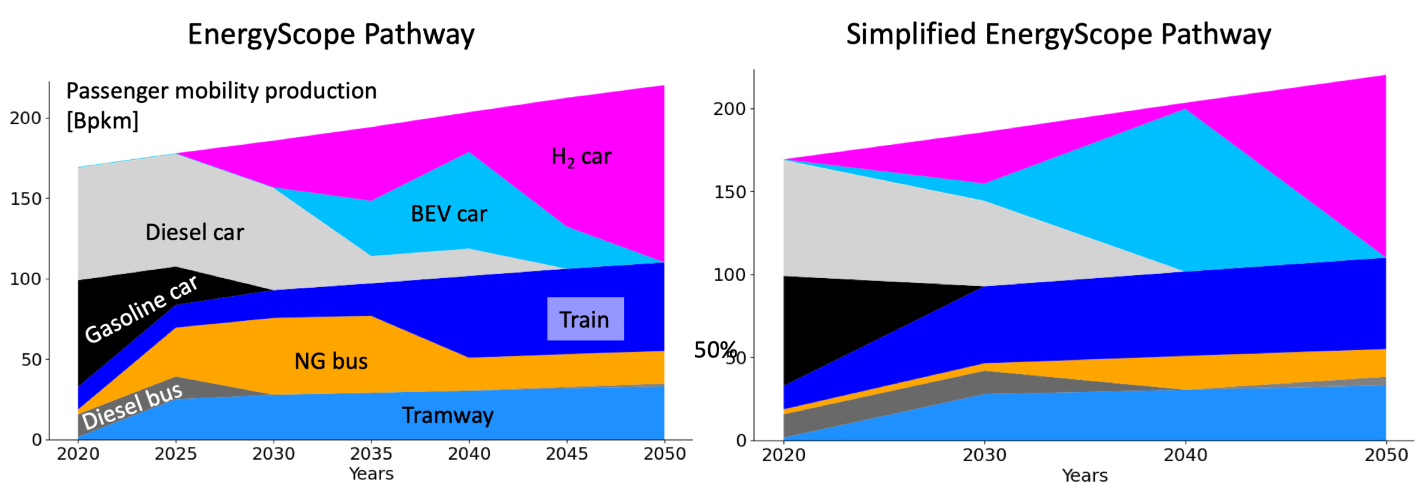

Figure B.6: Passenger mobility production during the transition with both models. Abbreviations : billions passenger-kilometer (Bpkm), natural gas (NG), hydrogen (H_2), battery electric vehicle (BEV).

Appendix C

Data for uncertainty analysis

C.1 Uncertainty characterisation

In his PhD thesis [7], S. Moret proposed a novel uncertainty characterisation method. With this method, he characterised the uncertain parameters of EnergyScope monthly, the precursor of EnergyScope TD. Since the input parameters of EnergyScope monthly are also input parameters of EnergyScope TD and EnergyScope Pathway, the uncertainty characterisation he performed on those input parameters will be used for the uncertainty analysis of this master thesis.

This novel uncertainty characterisation method determines the range of an uncertain parameter based on multiple sources: existing models that can be used to compute this parameter, ranges already proposed in the literature, existing forecasts, errors made in past forecasts, historical data and the influence of the decision-makers on this parameter. If one of those sources is available, then the range is calculated based on the collected data. If none of those sources is available, then the parameter range is approximated by the range of a similar parameter or a qualitative range.

Figure C.1 details the uncertainty characterisation of the EnergyScope input parameters. Only the uncertain parameters taken into account either in the uncertainty quantification or the robust optimisation, performed in this master thesis, are shown. In practice, the uncertainty on the input parameters will be represented by a uniform distribution in their range. A uniform distribution is used by default because the probability density functions (PDFs) of those parameters are not known.

Table C.1: Table of the uncertainty characterisation of the EnergyScope Pathway model input parameters, from the PhD thesis of S. Moret [7]. The uncertain parameters are divided into categories. Uncertainty is characterised by one representative parameter per category. The range of a parameter is defined from its nominal value. Abbreviations: photovoltaic (PV), fuel cell (FC), district heating network (DHN), decentralised (DEC), natural gas (NG).

Category	Representative parameter	Range from the nominal value
Annual household end-use energy demand	$endUses_{year}$(HH)	[−6.9% ; 4.3%]
Annual services end-use energy demand	$endUses_{year}$(S)	[−7.4% ; 4.1%]
Annual industry end-use energy demand	$endUses_{year}$(I)	[−10.5% ; 5.9%]
Annual transport end-use energy demand	$endUses_{year}$(TR)	[−3.4% ; 3.4%]
Efficiency of mature[a] and standard[b] technologies	$\eta(Boilers)$	[−5.7% ; 5.7%]
Efficiency of mature[a] and customised[b] technologies	η(GASOLINE CAR)	[−20.6% ; 20.6%]
Efficiency of new[a] and standard[b] technologies	η(PV)	[−20.8% ; 20.8%]
Efficiency of new[a] and customized[b] technologies	η(FC CAR)	[−28.7% ; 28.7%]
Resources availability	$avail$(WOOD)	[−32.1% ; 32.1%]
Maximum technology capacity	f_{max}(PV)	[−24.1% ; 24.1%]
Investment cost of mature technologies	c_{inv}(DEC NG BOILER)	[−21.6% ; 21.6%]
Investment cost of new technologies	c_{inv}(PV)	[−39.6% ; 39.6%]
	c_{inv}(NUCLEAR)	[−21.6% ; 119.3%]
	c_{inv}(HYDRO DAM)	[−21.6% ; 73.8%]
Investment cost of other technologies	c_{inv}(Thermal plants)	[−21.6% ; 25%]
	c_{inv}(WIND)	[−21.6% ; 22.9%]
	c_{inv}(DHN)	[−39.3% ; 39.3%]
	c_{inv}(geothermal)	[−39.7% ; 62.1%]
Local resources cost	c_{op}(WOOD)	[−2.9% ; 2.9%]
Imported resources cost	c_{op}(NG)	[−47.3% ; 89.9%]
Hourly capacity factor	$c_{p,t}$(PV)	[−11.1% ; 11.1%]

[a] A technology is classified as mature or new based on its stage of development.

[b] A technology is classified as standard or customised based on its level of customisation. For example, a boiler is a standard technology as it is not a customised good but a car is a customised technology as it is a customised good.

C.2 Uncertain parameters for uncertainty quantification

Table C.2: Name, description and uncertainty range of the uncertain parameters for the uncertainty quantification of section 3.3.2.

Parameter name	Description	Range from the nominal value
EU_HH	annual household end-use energy demand	[−6.9% ; 4.3%]
EU_S	annual services end-use energy demand	[−7.4% ; 4.1%]
EU_I	annual industry end-use energy demand	[−10.5% ; 5.9%]
EU_TR	annual transport end-use energy demand	[−3.4% ; 3.4%]
avail_elec	imported electricity availability	[−32.1% ; 32.1%]
avail_biomass	biomass availability	[−32.1% ; 32.1%]
avail_coal	coal availability	[−32.1% ; 32.1%]
c_op_fossil_car	price of diesel and gasoline	[−47.3% ; 89.9%]
c_op_fossil_other	price of natural gas (NG), liquid fuel oil (LFO) and uranium	[−47.3% ; 89.9%]
c_op_elec	price of imported electricity	[−47.3% ; 89.9%]
c_op_synfuels	price of hydrogen (H_2), synthetic natural gas (SNG) and synthetic liquid fuel (SLF)	[−47.3% ; 89.9%]
c_op_biofuels	price of bioethanol and biodiesel	[−47.3% ; 89.9%]
c_op_local	price of local resources (biomass, waste, coal)	[−2.9% ; 2.9%]
c_inv_PV	price of photovoltaic (PV) panels	[−39.6% ; 39.6%]
c_inv_wind_onshore	price of onshore wind turbines	[−21.6% ; 22.9%]
c_inv_wind_offshore	price of offshore wind turbines	[−21.6% ; 22.9%]
c_inv_th_plants	price of thermal power plants (CCGT, co-generation power plants)	[−21.6% ; 25%]
c_inv_heat_old	price of old heating technologies (fossil fuel boiler)	[−21.6% ; 21.6%]
c_inv_heat_new	price of new heating technologies (electric heater, thermal solar panel, advanced co-generation power plant)	[−39.6% ; 39.6%]
c_inv_HP	price of heat pumps	[−39.6% ; 39.6%]
c_inv_TR_old	price of old technologies for passenger and freight mobility (diesel and gasoline transport, train, tramway)	[−21.6% ; 21.6%]
c_inv_TR_new	price of new technologies for passenger and freight mobility (electric, NG and H_2 transport)	[−39.6% ; 39.6%]
c_inv_st_th	price of thermal storage technologies	[−39.6% ; 39.6%]
c_inv_st_elec	price of electricity storage technologies	[−39.6% ; 39.6%]
c_inv_st_other	price of other storage technologies (seasonal H_2, NG and SLF storage)	[−39.6% ; 39.6%]
f_max_PV	photovoltaic (PV) potential	[−24.1% ; 24.1%]
f_max_windON	onshore wind turbines potential	[−24.1% ; 24.1%]
f_max_windOFF	offshore wind turbines potential	[−24.1% ; 24.1%]
cpt_PV	solar energy hourly availability	[−11.1% ; 11.1%]
cpt_Winds	wind hourly availability	[−11.1% ; 11.1%]
eff_mat_std	efficiency of mature and standard technologies[a] (old technologies except for diesel and gasoline cars)	[−5.7% ; 5.7%]
eff_mat_cust	efficiency of mature and custom[a] technologies (diesel and gasoline car)	[−20.6% ; 20.6%]
eff_new_std	efficiency of new and standard[a] technologies (new technology except for new cars)	[−20.8% ; 20.8%]
eff_new_cust	efficiency of new and custom[a] technologies (electric, NG and H_2 cars)	[−28.7% ; 28.7%]

[a]A technology is classified as mature or new based on its stage of development and is classified as standard or custom based on its level of customisation. For example, a fossil fuel boiler is a mature and standard technology as the technology is well-known nowadays and it is not a customised good. On the contrary, a hydrogen car is a new and customised technology.

Appendix D

Robust optimisation

D.1 Uncertain parameters

The uncertain parameters for the robust optimisation of section 4.2 are resumed in the following table.

Table D.1: Name, description and uncertainty range of the uncertain parameters for the robust optimisation of section 4.2.

Parameter name	Description	Range from nominal value
EU	end-use energy demand	[−8.2% ; 8.2%]
avail_elec	imported electricity availability	[−32.1% ; 32.1%]
avail_local	local resources availability (biomass, coal)	[−32.1% ; 32.1%]
c_op_fossil	price of fossil fuels	[−47.3% ; 89.9%]
c_op_elec	price of imported electricity	[−47.3% ; 89.9%]
c_op_biosynfuels	price of biofuels and synthetic fuels	[−47.3% ; 89.9%]
c_op_local	price of local resources (biomass, waste, coal)	[−2.9% ; 2.9%]
c_inv_PV	price of photovoltaic (PV) panels	[−39.6% ; 39.6%]
c_inv_wind	price of wind turbines	[−21.6% ; 22.9%]
c_inv_th_plants	price of thermal power plants (CCGT, co-generation power plants)	[−21.6% ; 25%]
c_inv_heat_old	price of old heating technologies (fossil fuel boiler)	[−21.6% ; 21.6%]
c_inv_heat_new	price of new heating technologies (electric heater, thermal solar panel, advanced co-generation power plant)	[−39.6% ; 39.6%]
c_inv_TR_old	price of old technologies for passenger and freight mobility (diesel and gasoline transport, train, tramway)	[−21.6% ; 21.6%]
c_inv_TR_new	price of new technologies for passenger and freight mobility (electric, NG and H_2 transport)	[−39.6% ; 39.6%]
cpt_ren	renewable energy hourly availability	[−11.1% ; 11.1%]
eff_mat_std	efficiency of mature and standard technologies[a] (old technologies except diesel and gasoline car)	[−5.7% ; 5.7%]
eff_mat_cust	efficiency of mature and custom[a] technologies (diesel and gasoline car)	[−20.6% ; 20.6%]
eff_new_std	efficiency of new and standard[a] technologies (new technologies except new cars)	[−20.8% ; 20.8%]
eff_new_cust	efficiency of new and custom[a] technologies (electric, NG and H_2 cars)	[−28.7% ; 28.7%]

[a]A technology is classified as mature or new based on its stage of development and is classified as standard or custom based on its level of customisation. For example, a fossil fuel boiler is a mature and standard technology as the technology is well-known nowadays and it is not a customised good. On the contrary, a hydrogen car is a new and customised technology.

D.2 Simplifications applied to the Simplified EnergyScope Pathway model

The robust optimisation is computationally expensive even with the Simplified EnergyScope Pathway model. This is why some storage technologies will not be used during the robust optimisation since storage technologies are the main reason why the model is computationally expensive.

The daily DHN storage and the battery of the plug-in hybrid electric vehicle (PHEV) are removed from the model because they are never used during the uncertainty quantification performed in section 3.3.2.

The pumped hydro storage (PHS) is removed, even though it is fully used during the uncertainty quantification. The reason is that its capacity is limited at 6.5 GWh which is low compared to the average installed capacity of lithium batteries during the uncertainty quantification (60 GWh). Suppressing the PHS decreases drastically the computational time and does not influence much the total transition cost. As an example, for the basic scenario analysed in section 2.2, the computational time decreases from 347 to 239 seconds without PHS and the total transition cost increases by only 0.13%.

D.3 Decision variables

The decision variables for the robust optimisation are the maximum capacity f_{max} of technologies that can be installed during the transition, as explained in section 4.1. This section will explain the methodology to chose which technology will be a decision variable for the robust optimisation. The overall methodology is illustrated in Figure D.1. The methodology consists of three phases :

1. The determination of the first backup technologies
2. The determination of the decision variables range
3. The removal of insignificant technologies from the pool of candidate decision variables

First phase : Backup technologies

In order to create the *Big PCE*, the Simplified EnergyScope Pathway model will be evaluated in several samples of decision variables and uncertain parameters, as explained in section 4.1. In some samples, it can occur that every decision variables of a sector are closed to 0. This would result in an infeasible problem. Therefore, some technologies must not be constrained and will supply the demand on their own if the others can not. Let's take an example : The maximum capacity of PV panels, onshore wind turbines and offshore wind turbines are decision variables. If all those technologies are fixed to 0 in a sample, then CCGTs are used as backup to supply the entire electricity demand. Therefore, the maximum capacity of CCGT must not be a decision variable. Otherwise, the maximum capacity of CCGT could also be close to 0 and no technologies will be available to supply the electricity demand.

Furthermore, two backup technologies will be chosen for each sector, except for the electricity sector. Two backups is better than one because one technology can not work all the time. Every technology has a c_p factor which represents the downtime of a technology during a year. Choosing only one technology would therefore result in an infeasible problem, or in an excessive amount of storage technologies to supply the demand during the backup technology downtimes.

In addition, at least one of the backup technology must be unlimited in potential capacity and use an

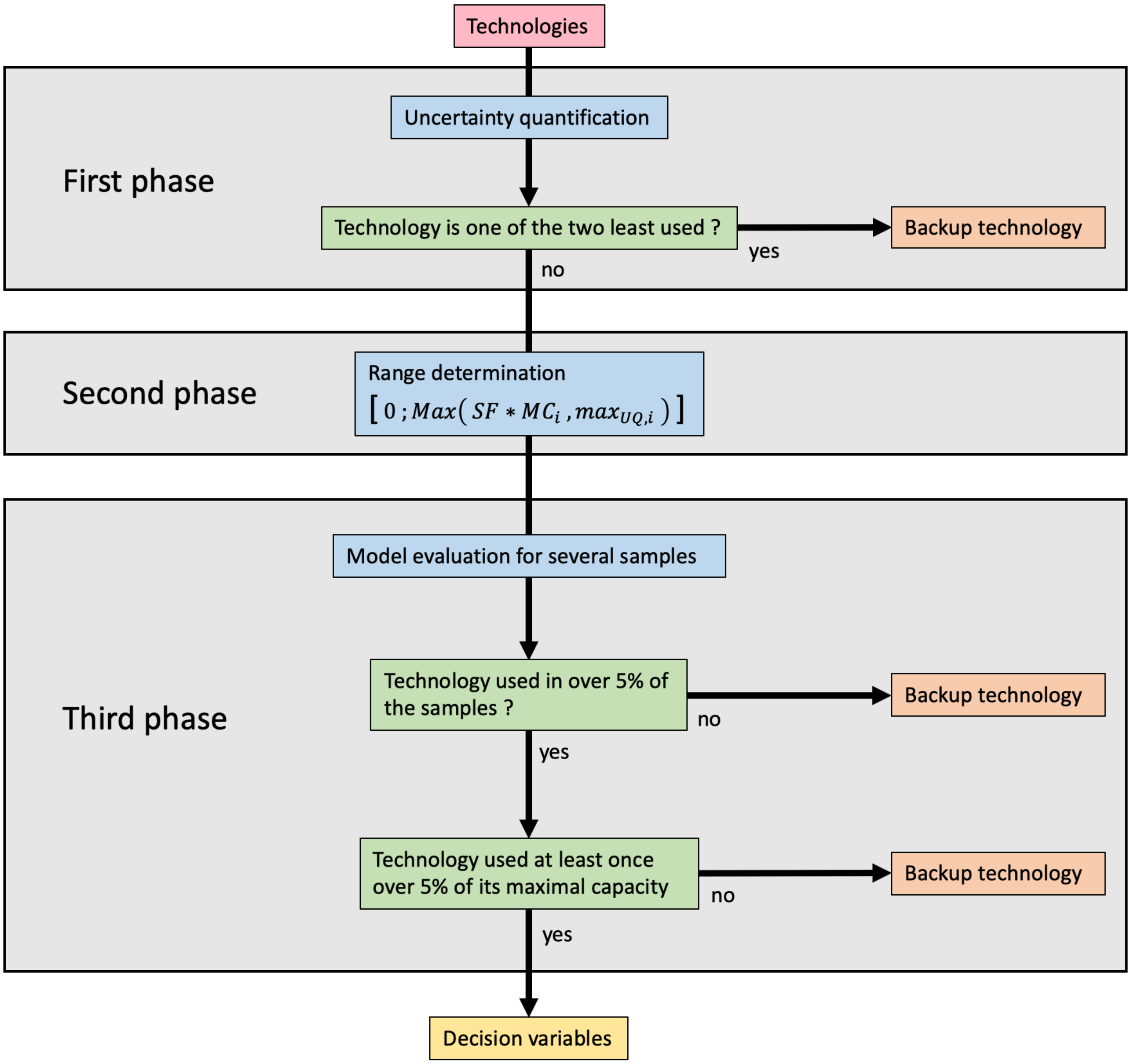

Figure D.1: Methodology to chose the decision variables for the robust optimisation. The first phase finds the backup technologies by looking at the technologies used during an uncertainty quantification, made beforehand. The second phase computes the range of the candidate decision variables. The third phase evaluates the model in several samples, by varying the uncertain parameters and the candidate decision variables, to check which technologies are used. If a technology is deemed useless, based on the two criteria, then it is removed from the pool of candidate decision variables. In the end, this methodology provides the important technologies to consider as decision variables and their ranges.

unlimited resource. This ensures that the problem is feasible, by having a technology that has no limit to meet the demand (except for the downtime as discussed above). For example, wood boilers and wood cogeneration power plants use wood which has a limited availability. Therefore, if one of them is a backup technology of the low temperature (LT) heat sector, the other can not be.

If more than two technologies could be the backup technologies of a sector, the two less used technologies in the uncertainty quantification performed in section 3.3.2 will be designated as the backup technology of the corresponding sector. The two less used are chosen in order to keep the most important technologies as decision variables for the robust optimisation. The backup technologies will now be discussed for each sector.

Electricity sector

The backup technology must be able to supply the entire demand. Thus, it is preferable to choose a technology that has no capacity limit. Technologies using renewable energy (PV and wind turbines) have a limited capacity in Belgium. Therefore, it is preferable that these technologies are not backup technologies. CCGT will be the backup technology since there is no limit on the capacity that can be installed in Belgium and the resource used in CCGT is natural gas, which is an unlimited resource in the model.

Moreover, CCGT is the only backup technology for the electricity sector. This is due to multiple reasons. Firstly, there are few technologies in the electricity sector. Nuclear and coal power plants can not be used. It leaves the model with only renewable energy and CCGT in the electricity sector. Secondly, electricity can be imported during the CCGT downtime if no other technologies can meet the demand. Thirdly, two backup technologies in other sector are cogeneration of heat and power (CHP) that produce electricity (waste CHP in the high temperature heat sector and advanced gas CHP in the decentralised low temperature heat sector).

The candidate decision variables of the electricity sector are the maximum capacity of PV, of onshore and offshore wind turbines. Geothermal capacity is set to 0 because of its limited availability and the scarcity of data [6]. The hydraulic power plants are set to their limit (0.115 GW) but are not taken into account in the robust optimisation because of this low potential.

High temperature heat sector

The first backup technology is the waste CHP in order to respect the constraint on the consumption of waste. Indeed, all the available waste is forced to be consumed during the time period of the transition. Therefore, a technology using waste needs to be unlimited in any case. Moreover, waste CHP is chosen over waste boiler because it is less used in the uncertainty quantification. The second backup technology is the liquid fuel oil (LFO) boiler. This technology is chosen because it is the less used technology with unlimited capacity and resource in the uncertainty quantification. The other technologies of the high temperature heat sector are in the pool of candidate decision variables.

DHN low temperature heat sector

The first backup technology of this sector is the district heating network (DHN) LFO boiler. It is the less used technology with unlimited capacity and resources during the uncertainty quantification. The second backup technology is the wood boiler because it is never used in the uncertainty quantification. The other technologies of this sector are in the pool of candidate decision variables, except for the technology using a geothermal source to produce low temperature heat, for the same reason as for geothermal power plant in the electricity sector.

DEC low temperature heat sector

The two backup technologies of the decentralised LT heat sector are the advanced gas CHP and the LFO boiler because these two technologies are not used during the uncertainty quantification. Moreover, these technologies use an unlimited resource in the model. The other technologies of this sector are in the pool of candidate decision variables.

Passenger mobility

Since the private and public passenger mobility must both meet a minimum percentage of the demand, one backup technology must be in the private passenger mobility sector and the other one must be in the public passenger mobility sector. The two backup technologies are the fuel cell bus and the natural gas car because those two technologies are the less used in the uncertainty quantification. The rest of the technologies of this sector are candidates for decision variables.

Freight mobility

The freight mobility is divided between the boat, the road and the train part. Those 3 parts must meet a minimum percentage of the demand. This is why a backup technology is needed for each one of those parts. For the boat part, the backup technology is the natural gas boat because it is the less used boat during the uncertainty quantification. For the road part, the backup technology is the natural gas truck because it is the less used during the uncertainty quantification. For the train part, there is only one technology (freight train). Therefore, this technology must be a backup technology. The other technologies are in the pool of candidate decision variables.

Infrastructure and storage technologies

The infrastructure and storage technologies are not taken into account for the robust optimisation. There are 10 infrastructure technologies and 7 available storage technologies in the model for the robust optimisation. Adding 17 decision variables to the robust optimisation will be computationally unaffordable. Therefore, the infrastructure and the storage technologies will not be part of the robust optimisation as they will not be in the pool of candidate decision variables.

Second phase : Ranges of the decision variables

The decision variables need to be bounded to use the multi-objective optimisation algorithm NSGA-II. In this section, the methodology to find the range of the decision variables is described. Then, the ranges are described for each type of technology.

If a technology has a maximum potential capacity in Belgium, its range is simply from 0 to this maximum potential capacity. Otherwise, the purpose of the ranges is to go from 0 to the required capacity to supply theoretically the entire demand. For example, let's say that 3 GW of gas boiler is installed and meet 50% of the low temperature (LT) heat demand. In theory, the entire LT heat demand could be met by 6 GW of gas boiler. The range of the maximum installed capacity of gas boilers will consequently go from 0 to 6 GW. This maximum capacity, theoretically required, is calculated from the installed capacity in the basic scenario, analysed in section 2.2, and from the percentage of the demand met by this technology. In general, the year 2050 was preferred because of the demands' increase over time (except for the high temperature heat sector). The maximum capacity theoretically required (MC) of the i-th technology is calculated as

$$MC_i = F_i \cdot f_{perc,i} \tag{D.1}$$

with F_i the installed capacity of the i-th technology in 2050 and $f_{perc,i}$ the energy produced by the i-th technology divided by the sum of the energy produced by technologies of the same type.

Nevertheless, the basic scenario analysed in section 2.2 is a deterministic scenario. In reality, the parameters are uncertain. If the uncertain energy demands are higher than the energy demands in the deterministic case, then a higher capacity would be needed to supply the energy demands.

To take this into account, a safety factor of 1.1 is applied to the MCs found. This safety factor is justified by the fact that, in the uncertainty quantification, the higher possible increase of the energy demands is +8.2% for the industry demand. Moreover, if once during the uncertainty quantification a technology has a capacity higher than 1.1 times the MC found for this technology, then this capacity will be the maximum value of the range. The range of a technology i is therefore calculated as follows

$$[\,0 \quad ; \quad Max(1.1 \cdot MC_i \, , \, max_{UQ,i})\,] \tag{D.2}$$

with $max_{UQ,i}$ the maximum installed capacity of the i-th technology in the uncertainty quantification performed in section 3.3.2.

Electricity sector

All the candidate decision variables are technologies using renewable energy. Those technologies have a maximum potential capacity in Belgium which will be the upper limit of these technologies : 59.175 GW for photovoltaic (PV) panel, 10 GW for onshore wind turbines and 3.5 GW for offshore wind turbines.

High temperature heat sector

The upper limit with equation D.2 is 10 GW. An exception is made for the industrial electric heaters which are used up to 16 GW during the uncertainty quantification.

DHN low temperature heat sector

In this sector, only the electric heat pump is really used. Its upper limit is 19 GW. The rest of the technologies are rarely used in the uncertainty quantification. Consequently, no upper bound can be identified with the methodology. Therefore, for the sake of simplicity, a qualitative range of 20 GW is taken for every technology of the DHN sector.

DEC low temperature heat sector

The upper limit of the decentralised electric heat pump is 38 GW with equation D.2. The same upper limit is applied to the thermal heat pump.

For the rest of the technologies, their upper limits are determined with the installed capacity in the year 2020 of the basic scenario since only electric heat pumps are installed during this scenario transition. By doing so, the upper limit of every decentralised technology, except the heat pump, are 60 GW.

Passenger mobility

With equation D.2, the upper limit of the tramways and trolleys is 12 Mpkm/h, the upper limit of buses is 50 Mpkm/h, the upper limit for the public train is 25 Mpkm/h and the upper limit for the cars is 275 Mpkm/h.

Freight

With equation D.2, the upper limits for the boats and the trucks are, respectively, 35 Mtkm/h and 70 Mtkm/h.

Third phase : Elimination of insignificant technologies

The third phase consists of identifying the technologies that are rarely used during the transition, even when uncertainty is taken into account. Such a technology will be removed from the pool of candidate decision variables. The purpose is to keep only the useful technologies in order to decrease the computational time and improve the accuracy of the Big PCE, required for the robust optimisation.

To identify which technology is rarely used, the Simplified EnergyScope Pathway will be evaluated in multiple samples where the decision variables and the uncertain parameters are varied, just like it must be done to build the Big PCE. A latin hypercube sampling (LHS) method is used to create those samples. The number of samples has been chosen as the number of samples that would be required to build a 50% sparse PCE depending on the decision variables and the uncertain parameters. As an example, in this case, 41 technologies are in the pool of candidates for the decision variables and 19 uncertain parameters are taken into account (see Table D.1). With equation 3.20 and a second-order PCE, the required number of samples is 3782 for a full PCE and thus 1891 for a 50% sparse PCE.

Based on those model evaluations, a candidate for decision variables is kept if the associated technology is used in more than 5% of the model evaluations and if the technology has an installed capacity during the transition over 5% of its maximum capacity in at least one model evaluation. If a technology does not respect those two criteria, then it is removed from the pool of candidates. For example, a technology that has a upper limit of 50 GW is deemed useless if it is used in less than 5% of the model evaluations or if the maximum capacity installed during the transition is below 2.5 GW.

The technologies deemed significant at the end of this third phase are resumed in Table D.2 and constitute the decision variables of the robust optimisation performed in section 4.2.

Finally, some decision variables are subject to a constraint which forces, for each individual, the sum of the decision variables, with the same letter in Table D.2, to be below the individual limit of those decision variables. For example, the sum of the decision variables of trucks must be below 70 Mtkm/h which is the limit for each truck. This constraint prevents that different technologies are used during different model evaluations for the uncertainty quantification of an individual, as explained in section 4.1.

Table D.2: Technologies taken as decision variables (maximum capacity of those technologies) and their corresponding range for the robust optimisation. Some technologies are subject to a constraint forcing their sum to be below the individual limit of those technologies, as explained above. The technologies with the same letters are subject to the same constraint.

Sectors	Decision variables / Technologies	Ranges [GW][a]	Constraint
Electricity	PV	[0 ; 59.175]	g[b]
	WIND ONSHORE	[0 ; 10]	-
	WIND OFFSHORE	[0 ; 3.5]	-
HT heat	IND COGEN GAS	[0 ; 10]	a
	IND COGEN WOOD	[0 ; 10]	a
	IND BOILER WASTE	[0 ; 10]	a
	IND BOILER WOOD	[0 ; 10]	a
	IND BOILER GAS	[0 ; 10]	a
	IND BOILER COAL	[0 ; 10]	a
	IND DIRECT ELEC	[0 ; 16]	-
DHN LT heat	DHN HP ELEC	[0 ; 19]	-
	DHN COGEN GAS	[0 ; 20]	b
	DHN COGEN BIO HYDROLYSIS	[0 ; 20]	b
	DHN SOLAR	[0 ; 20]	g[b]
DEC LT heat	DEC HP ELEC	[0 ; 38]	-
	DEC THHP GAS	[0 ; 38]	-
	DEC COGEN GAS	[0 ; 60]	c
	DEC ADVCOGEN H2	[0 ; 60]	c
	DEC BOILER GAS	[0 ; 60]	c
	DEC BOILER WOOD	[0 ; 60]	c
	DEC SOLAR	[0 ; 60]	g[b]
Passenger mobility	TRAMWAY TROLLEY	[0 ; 12]	-
	BUS COACH DIESEL	[0 ; 50]	d
	BUS COACH HYDIESEL	[0 ; 50]	d
	BUS COACH CNG STOICH	[0 ; 50]	d
	TRAIN PUB	[0 ; 25]	-
	CAR DIESEL	[0 ; 275]	e
	CAR GASOLINE	[0 ; 275]	e
	CAR HEV	[0 ; 275]	e
	CAR BEV	[0 ; 275]	e
	CAR FUEL CELL	[0 ; 275]	e
Freight mobility	BOAT FREIGHT DIESEL	[0 ; 35]	-
	TRUCK DIESEL	[0 ; 70]	f
	TRUCK FUEL CELL	[0 ; 70]	f
	TRUCK ELEC	[0 ; 70]	f

[a] [Mpkm/h] (millions of passenger-km per hour) for passenger and [Mtkm/h] (millions of ton-km per hour) for freight.

[b] This constraint is different, it limits the area of solar panel to 250km^2 in the same way as in the Simplified EnergyScope Pathway model. See table 1.1 for more informations.

Bibliography

[1] Ove Hoegh-Guldberg, Daniela Jacob, M Bindi, S Brown, I Camilloni, A Diedhiou, R Djalante, K Ebi, F Engelbrecht, J Guiot, et al. Impacts of 1.5 c global warming on natural and human systems. *Global warming of 1.5 C. An IPCC Special Report*, 2018.

[2] United Nations Framework Convention on Climate Change (UNFCCC). The paris agreement. `https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement`.

[3] Bob Dudley et al. Bp statistical review of world energy 2019. *London, UK*, 2020.

[4] Eurostat. Energy data - 2020 edition. 2020.

[5] Matteo Giacomo Prina, Matteo Lionetti, Giampaolo Manzolini, Wolfram Sparber, and David Moser. Transition pathways optimization methodology through energyplan software for long-term energy planning. *Applied Energy*, 235:356–368, 2019.

[6] Gauthier Limpens. *Optimisation of energy transition pathways - application to the case of Belgium*. PhD thesis, UCLouvain, 2021.

[7] Stefano Moret. Strategic energy planning under uncertainty. Technical report, EPFL, 2017.

[8] Gauthier Limpens, Stefano Moret, Hervé Jeanmart, and Francois Maréchal. Energyscope td: A novel open-source model for regional energy systems. *Applied Energy*, 255:113729, 2019.

[9] Victor Codina Gironès, Stefano Moret, François Maréchal, and Daniel Favrat. Strategic energy planning for large-scale energy systems: A modelling framework to aid decision-making. *Energy*, 90:173–186, 2015.

[10] Gauthier Limpens, Stefano Moret, Hervé Jeanmart, and Francois Maréchal. Energyscope td: a novel open-source model for regional energy systems. supplementary material. Available online in the repository of EnergyScope TD : `https://github.com/energyscope/EnergyScope/tree/v2.0`. last consulted on 14/05/2021.

[11] Gauthier Limpens and Hervé Jeanmart. Electricity storage needs for the energy transition: An eroi based analysis illustrated by the case of belgium. *Energy*, 152:960–973, 2018.

[12] Pantelis Capros, A De Vita, N Tasios, P Siskos, M Kannavou, A Petropoulos, S Evangelopoulou, M Zampara, D Papadopoulos, Ch Nakos, et al. Eu reference scenario 2016-energy, transport and ghg emissions trends to 2050. 2016.

[13] Kris Poncelet, Erik Delarue, Daan Six, and William D'haeseleer. Myopic optimization models for simulation of investment decisions in the electric power sector. In *2016 13th International Conference on the European Energy Market (EEM)*, pages 1–9. IEEE, 2016.

[14] Elia Group. Belgium exported more electricity than it imported in 2019. *PRESS RELEASE | Brussels,*

08/01/2020 08:00 CET.

[15] Uwe Arnold and Özgür Yildiz. Economic risk analysis of decentralized renewable energy infrastructures–a monte carlo simulation approach. *Renewable Energy*, 77:227–239, 2015.

[16] Luca Urbanucci and Daniele Testi. Optimal integrated sizing and operation of a chp system with monte carlo risk analysis for long-term uncertainty in energy demands. *Energy conversion and management*, 157:307–316, 2018.

[17] Laetitia Uwineza, Hyun-Goo Kim, and Chang Ki Kim. Feasibilty study of integrating the renewable energy system in popova island using the monte carlo model and homer. *Energy Strategy Reviews*, 33:100607, 2021.

[18] Abdollah Younesi, Hossein Shayeghi, Amin Safari, and Pierluigi Siano. Assessing the resilience of multi microgrid based widespread power systems against natural disasters using monte carlo simulation. *Energy*, 207:118220, 2020.

[19] Juan Zhang, Junping Yin, and Ruili Wang. Basic framework and main methods of uncertainty quantification. *Mathematical Problems in Engineering*, 2020.

[20] Diederik Coppitters, Ward De Paepe, and Francesco Contino. Surrogate-assisted robust design optimization and global sensitivity analysis of a directly coupled photovoltaic-electrolyzer system under techno-economic uncertainty. *Applied Energy*, 248:310–320, 2019.

[21] Diederik Coppitters, Ward De Paepe, and Francesco Contino. Robust design optimization and stochastic performance analysis of a grid-connected photovoltaic system with battery storage and hydrogen storage. *Energy*, 213:118798, 2020.

[22] Cong Wang, Ivo Martinac, and Alessandro Magny. Multi-objective robust optimization of energy systems for a sustainable district in stockholm. In *14th Conference of International Building Performance Simulation Association, BS 2015, 7 December 2015 through 9 December 2015*, 2015.

[23] Sebastian Burhenne, Dirk Jacob, and Gregor P Henze. Sampling based on sobol'sequences for monte carlo techniques applied to building simulations. In *Proc. Int. Conf. Build. Simulat*, pages 1816–1823, 2011.

[24] Martin Roberts. The unreasonable effectiveness of quasirandom sequences. *Online article available at http://extremelearning. com. au/unreasonable-effectiveness-of-quasirandom-sequences*, 2018.

[25] L Chrisman. Latin hypercube vs. monte carlo sampling. *Lumina Blog*, 2014.

[26] Atharv Bhosekar and Marianthi Ierapetritou. Advances in surrogate based modeling, feasibility analysis, and optimization: A review. *Computers & Chemical Engineering*, 108:250–267, 2018.

[27] Ward De Paepe, Diederik Coppitters, Simon Abraham, Panagiotis Tsirikoglou, Ghader Ghorbaniasl, and Francesco Contino. Robust operational optimization of a typical micro gas turbine. *Energy Procedia*, 158:5795–5803, 2019.

[28] M Ebden. Gaussian processes for regression: A quick introduction (robotics research group, university of oxford, 2008).

[29] Bruno Sudret. Polynomial chaos expansions and stochastic finite element methods. *Risk and reliability in geotechnical engineering*, pages 265–300, 2015.

[30] David Métivier, Marc Vuffray, and Sidhant Misra. Efficient polynomial chaos expansion for uncertainty quantification in power systems. *Electric Power Systems Research*, 189:106791, 2020.

[31] Simon Abraham, Mehrdad Raisee, Ghader Ghorbaniasl, Francesco Contino, and Chris Lacor. A robust and efficient stepwise regression method for building sparse polynomial chaos expansions. *Journal of Computational Physics*, 332:461–474, 2017.

[32] Mohammad H Moradi, Mehdi Hajinazari, Shahriar Jamasb, and Mahmoud Paripour. An energy management system (ems) strategy for combined heat and power (chp) systems based on a hybrid optimization method employing fuzzy programming. *Energy*, 49:86–101, 2013.

[33] WT Lu, C Dai, ZH Fu, ZY Liang, and HC Guo. An interval-fuzzy possibilistic programming model to optimize china energy management system with co2 emission constraint. *Energy*, 142:1023–1039, 2018.

[34] ND Sanders, RM Everson, JE Fieldsend, and AAM Rahat. A bayesian approach for the robust optimisation of expensive-to-evaluate functions. arxiv e-prints, page. *arXiv preprint arXiv:1904.11416*, 2019.

[35] Cong Dong, Guohe Huang, Yanpeng Cai, Guanhui Cheng, and Qian Tan. Bayesian interval robust optimization for sustainable energy system planning in qiqihar city, china. *Energy Economics*, 60:357–376, 2016.

[36] Giorgio Chiandussi, Marco Codegone, Simone Ferrero, and Federico Erminio Varesio. Comparison of multi-objective optimization methodologies for engineering applications. *Computers & Mathematics with Applications*, 63(5):912–942, 2012.

[37] Ning Zhao and Fengqi You. New york state's 100% renewable electricity transition planning under uncertainty using a data-driven multistage adaptive robust optimization approach with machine-learning. *Advances in Applied Energy*, 2:100019, 2021.

[38] Claire Nicolas, Olivier Bahn, Stéphane Tchung-Ming, and Erick Delage. *Robust energy transition pathways for global warming targets*. GERAD, École des hautes études commerciales, 2016.

[39] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197, 2002.

[40] Paolo Thiran and Aurélia Hernandez. Energyscope multi-cell : a novel open-source model for multi-regional energy systems and application to a 3-cell, low-carbon energy system. Ecole polytechnique de Louvain, Université catholique de Louvain, 2020. Prom. : Jeanmart, Hervé ; Limpens, Gauthier.

[41] ER Observ et al. Photovoltaic barometer-eurobserv'er-april 2020. 2020.

[42] Wind Europe. Wind energy in europe in 2019—trends and statistics. *Wind Europe: Brussels, Belgium*, 2020.

[43] ER Observ et al. Wind energy barometer-eurobserv'er-march 2020. 2020.

[44] European Commission. Statistical pocketbook 2020: Eu transport in figures, 2020.

[45] Service public fédéral Mobilité et Transports et al. Chiffres clés de la mobilité en belgique, 2020.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
École polytechnique de Louvain
Rue Archimède, 1 bte L6.11.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/epl**