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EnergyScope Pathway: an open-source model to optimise the energy transition pathways of a regional whole-energy system

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Acronyms

BEV battery electric vehicle.

CAPEX capital expenditure.

CCGT combined cycle gas turbine.

CHP combined heat and power.

CO_2 carbon dioxyde.

DHN district heating network.

EnergyScope TD EnergyScope Typical Days.

EUD end-use demand.

FC fuel cell.

GHG greenhouse gas.

GSA global sensitivity analysis.

GWP global warming potential.

HVC high value chemicals.

IEA International Energy Agency.

IPCC intergovernmental panel for climate change.

LCA life cycle assessment.

LCOE levelised cost of energy.

LFO light fuel oil.

LP linear programming.

OPEX operational expenditure.

PV photovoltaic.

TCO total cost of ownership.

TD typical day.

TSO transmission system operator.

VRES variable renewable energy sources.

Abstract

Due to the imperative nature of addressing climate change, the energy transition is currently underway, prompting the recognition of its urgency. Energy system optimisation models have emerged as crucial tools to assist policymakers in formulating laws and regulations that facilitate the transition towards carbon neutrality. While numerous models have been developed to explore various scenarios and define long-term objectives, only a few models focus on optimising the specific pathway to achieve these objectives. Many existing models lack the necessary time resolution to capture the integration of intermittent renewable energies; or are not open-source, creating a challenge in terms of transparency and reproducibility.

This paper introduces EnergyScope Pathway, an open-source and documented model that addresses these limitations. It specifically optimises investment strategies for the whole-energy system over a 30-year period, or more, and optimising its hourly operation. This approach allows for a comprehensive evaluation of the effective integration of intermittent renewable energy sources. The model has a concise and efficient formulation, enabling its execution on personal laptops within approximately 15 minutes. By applying the model to the case study of Belgium, which presents challenges due to limited potential for renewable energy, we illustrate the importance of four pillars: energy efficiency, renewable energies, sector coupling, electrification and imports. The result pave the way to a new and incremental tool to support decision makers. In comparison to non open-source models, we verified the model's results with similar studies and found consistency in terms of technico-economic estimations.

1 Introduction

While there is a vast consensus on the goal of achieving carbon neutrality by 2050, there is no unanimity on how to achieve it. Some advocate a —sometimes blind— faith in technological progress, while others advocate a major change —sometimes baseless— in consumption behaviour. Within the realm of technologies, debates range from advocating complete electrification of all energy requirements to merely replacing current fossil fuels with renewable alternatives. The energy transition pathway will be the result of a compromise between each of these views, where all the levers will be activated to a greater or lesser extent.

Energy system models of varying complexity are valuable tools for guiding policymakers and projecting future trends. These models enable the exploration of different energy scenarios and the assessment of their consequences based on the underlying assumptions. Specifically, techno-economic models play a crucial role in identifying technically feasible pathways for the energy transition while considering the associated economic costs. These models can be classified based on two key factors: technical resolution and simulation horizon, as illustrated in Figure 1.

Increasing the technical resolution of energy system models often comes at the expense of a shorter simulation horizon, and vice versa. For instance, day-ahead grid operation models prioritise accurate grid resolution and capacity reserves for uncertainties, but they may not incorporate long-term market trends. Different model classes cater to various needs, with decreasing technical resolution. These include machine-level control, network dispatch, unit commitment, maintenance, power plant expansion, planning for new infrastructure, and scenario analysis. Each class serves a specific purpose, from fine-grained control within a machine to the exploration of multiple assumptions across different scenarios.

In accordance with the previous classification, models aimed at aiding decision-makers in the energy transition primarily fall under the categories of planning and scenario analysis, with a relatively lower technical resolution. Nonetheless, ensuring technical accuracy is of paramount importance to ensure the effective functionality of future energy systems. Hence, these models

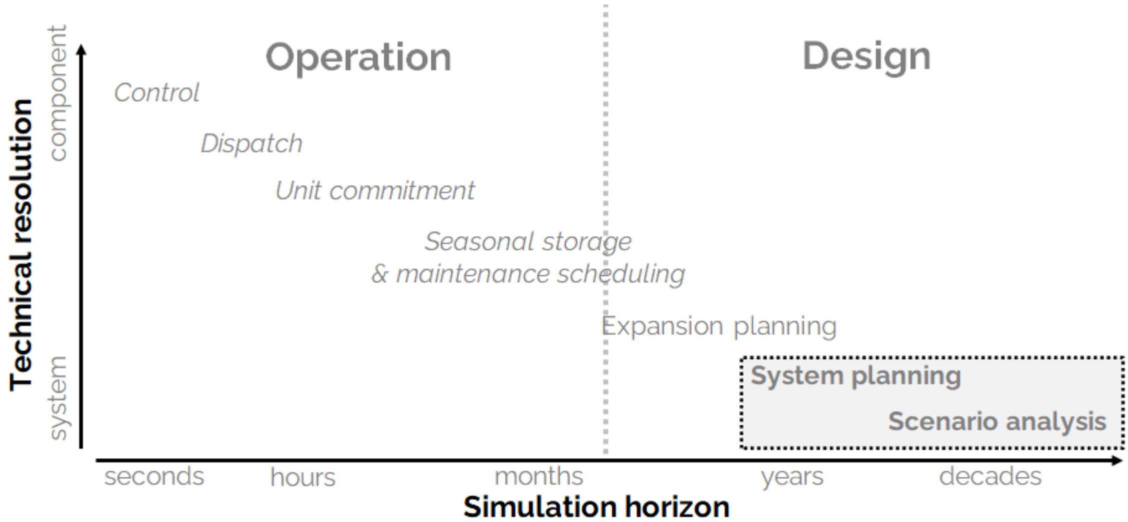

Figure 1: Model can be classified by their core focus: **Operation** or **Design**. These categories can be broken down into subcategories. This paper focuses on the system planning and scenario analysis models. Inspired from [1].

should meet the following requirements as a minimum: (i) assessment of intermittent renewable energy integration; (ii) accounting for all energy flows in different sectors, including the measurement of greenhouse gas emissions in the energy sector; (iii) exploration of all available options; (iv) consideration of investments throughout the transition process; and (v) ensuring a reasonable computation time for analysing different trajectories. Additionally, to enhance result reproducibility and user understanding, it is advantageous for such models to: (vi) maintain transparency and preferably be open-source, accompanied by collaborative documentation.

These requirements can be transposed into criteria that a model should match: (i) it should have an hourly resolution spanning a one-year time horizon; (ii) it should encompass the entire energy system, including all types of demands (such as heat, electricity, mobility, and non-energy[1]), as well as all resources, conversion processes, and storage technologies; (iii) it should optimise the system design, accounting for all the options; (iv) it should have a long-term investment horizon, spanning several decades; (v) its computational time should be reasonable, typically less than one hour on a personal laptop; (vi) it should be open-source, with accessible data and comprehensive documentation. These requirements are commonly found in reviews of energy system models. In 2010, Connolly et al. [4] reviewed 68 tools, considering similar criteria: (i-iv) and (vi), along with others such as the number of users and market equilibrium. In 2019, Prina et al. [5] reviewed 12 "*most established*" models, focusing on criteria (i-ii) and (iv). This review was followed by a classification where criteria (i-iv) were taken into account [6]. In 2021, Chang et al. [7] conducted a survey-based review of 42 models for energy transition modelling, covering all criteria except computational time. Based on these reviews, Table 1 compares models based on all the previous criteria except the computational time (v). Indeed, the latter is hard to compare as models aren't apply to the same case study and the information is rarely given. The table includes only the models that achieved partially at least four out of the five criteria. The authors endeavored to refresh the model's information by consulting the model's website and repository, yet there is a possibility that some information might have been overlooked or omitted inadvertently.

[1]Non-energy demand is often omitted in models while it represents up to 10% of worldwide energy demand and up to 20% in some countries [2]. Eurostat [3] defines the non-energy demand as '*energy products used as raw materials in different sectors, not consumed as a fuel or transformed into another fuel*'.

Table 1: Comparison of existing models that partially satisfy at least four of the six criteria (in alphabetical order). Legend: ✔criterion satisfied; ✓ criterion partially satisfied; ✗ criterion not satisfied. Data from [4–7].

Model	**Ref.**	**Hourly**	**Whole-energy**	**Optimis. invest. & operation**	**Pathway**	**Open-source**
Calliope	[8, 9]	✔	✔	✔	✗[a]	✔
COMPOSE	[10]	✔	✔	✔	✔	✓[b]
DER-CAM	[11, 12]	✔	✓[cd]	✔	✗[e]	✓[f]
DIETER	[13]	✔	✓[dg]	✔	✗[e]	✔
E2M2	[14]	✔	✓[cdh]	✔	✔	✗[i]
EMPIRE	[15]	✔	✗[cdgh]	✔	✔	✓[b]
Ener. Trans. Model	[16]	✔	✔	✗[j]	✔	✔
EnergyPLAN	[17]	✔	✔	✗[k]	✗[l]	✓[f]
energyRt	[18]	✔	✔	✓[m]	✔	✔
EnergyScope TD	[19]	✔	✔	✔	✗[l]	✔
Enertile	[20]	✔	✔[d]	✔	✔	✗[n]
ESO-XEL	[21]	✔	✗[cdgh]	✔	✔	✔
GENeSYS-MOD	[22]	✔	✔	✔	✔[o]	✔
H2RES	[24]	✔	✗[p]	✓[p]	✔	✔
iHOGA	[26]	✔	✗[cdgh]	✓[m]	✔	✓[b]
IMAKUS	[27]	✔	✓[cd]	✔	✔	✗[i]
OpenDSS	[28]	✔	✔	✗[k]	✔	✔
Plexos	[29]	✔	✓[q]	✔	✔	✗[i]
PyPSA	[31, 32]	✔	✔	✔	✓[r]	✔
RamsesR	[34]	✔	✓[cdh]	✔	✔	✔
ReEDS	[35]	✗[s]	✓[dgh]	✔	✔	✓[b]
TIMES	[36]	✔	✔	✔	✔	✔[t]

[a]Topic is being discussed in the chat of their repository but not yet included in their documentation.

[b]'*Free under some special conditions*'.

[c] Transport not accounted.

[d] Industry not accounted

[e] Not specified but time horizon is 1 year.

[f] Freeware.

[g] district heating network (DHN) not accounted.

[h] individual heating not accounted.

[i] Commercially (paid) licensed.

[j]The ETM is a simulation model with a simple merit order 'optimisation' for electricity, flex and heat.

[k] Simulation model.

[l] Yearly horizon without pathway.

[m] EnergyRT optimises investments only, while iHOGA conducts optimisation and simulation without specifying timing or scope.

[n]Only for internal use.

[o]Löffler et al. [22] applied a pathway transition, but the time resolution was increased to 12h and it uses 3 typical days over a year. [23] performed a multi-regional pathway (16 nodes) for the case of Germany from 2020 to 2050 with a time step of 5 years. However, the time resolution is 16 time slices representing 4 hours per day and one day per season.

[p] In their review in 2021, [25] classified H2RES as a simulation model on power sector only. In their work [24] presented a new version of H2RES claiming to optimise the power system and partially represent other sectors. Their study applied the model to a transition pathway for Croatia. In the conclusion, it is claimed '*H2RES offers practically unlimited potential for functionality expansion since it is an open-source program*' which open the doors for future developments to encompass new features.

[q]Doesn't account for all sector but allow to implement them according to [30].

[r][33] applied PyPSA to a whole energy system split in 37 nodes. Using a myopic approach, the model optimises the energy transition with a 3-hours resolution).

[s]Seasonal time slice.

[t]Model is now open-source with limited access to data [37].

From Table 1, four models almost check all the boxes (partially the pathway one): Calliope, GENeSYS-MOD, PyPSA and TIMES. The TIMES model, short for The Integrated MARKAL-EFOM System, is a well-established framework renowned for its capacity to generate comprehensive energy models. It encompasses a rich array of features, including support for multi-cell modeling, pathway analysis, full-scale representation of energy systems, and the consideration of market equilibrium dynamics, all of which facilitate thorough scenario exploration. This model has a widespread adoption and has been utilized by worldwide institutions such as the International Energy Agency (International Energy Agency (IEA)) or technical ones such as VITO (Vlaamse Instelling voor Technologisch Onderzoek) research institute in their research endeavors. Notably, TIMES was reported commercial in 2010 [4]. A more recent survey conducted in 2020-2021 confirmed that the model was using a commercial interface [7]. Recent developments by the IEA-ETSAP have resulted in a version that is compatible with open-source solver CBC. In various studies conducted in different regions, including Canada, Sweden, the EU, and Denmark, TIMES has been shown to utilize 12 to 32 time-slices annually [6]. It is noteworthy that Haydt et al. [38] conducted a study focusing on the electrical sector, using 288 time slices, equivalent to a 12-day time resolution, highlighting the sensitivity of results to time resolution. Regarding data accessibility, while some publications partially present the dataset used, the overall accessibility of TIMES data remains an area of ongoing inquiry [37]. Calliope is a '*tool that makes it easy to build energy system models*' at different geographical scale. Even if the framework offers the possibility of modelling multi-year systems, the authors didn't find a relevant publication on this topic. In fact, the model is typically employed for scenario analysis with a specific focus on the electricity system. Previous studies have used the model to investigate the phasing out of fossil and nuclear energies in a multi-regional UK power system [39]. More recently, the model has been applied to analyse a scenario of a multi-energy district in Switzerland [40]. Moreover, the model has been used with decades of weather data. However, its application has been limited to assessing the impact of inter-year variability in wind and PV on the results, rather than evaluating a transition pathway [41]. Similarly GENeSYS-MOD presents some limitations. This model is an application of the open-source energy modelling system (OSeMOSYS), itself represented as a model with a poor time discretisation and a heavy computational burden according to [5]. Löffler et al. [22] applied the model to the world by splitting it into 10 regions and most of the energy demand sectors. The time disaggregation can be chosen by the user, for their application they used representative years with three days and two time slice per day. Among the open-source models with an active community, PyPSA is one of the best-performing, with a large and active community, development at the state of the art, worldwide applications, and usage not only limited to academia. A study conducted by Bartholdsen et al. [23] centered on Germany employed a representation comprising 16 time slices for representative years. This choice was substantiated by the work of Welsch et al. [42], which demonstrated that this level of temporal granularity yields consistent results in comparison to hourly time resolution over a year. However, it is noteworthy that the utilization of a limited number of time slices may simplify the optimization of storage technologies, especially those designed for inter-month energy storage. This simplification can be viewed as a pragmatic approach to reduce the computational burden while over-simplifying the challenge of accurately integrating intermittent renewable energy sources. Furthermore, PyPSA, a modeling framework recognized for its robustness and active user community, has also been employed to investigate scenarios related to myopic transitions [33]. Hence, it is worth noting that while Calliope, OSeMOSYS, PyPSA and TIMES frameworks have the potential to be used for evaluating a transition pathway, the authors have not come across any publication that explicitly demonstrates their application to such cases with an hourly time resolution over significant time slices.

Hence, it appears that none of the models of Table 1 fully meet all five criteria outlined in the table, topped with the additional consideration of acceptable computational time. This observation is consistent with the findings presented in [5] who identified two approaches for optimising the energy transition pathway based on the six criteria. The first approach involves running a snapshot model multiple times using an algorithm that optimises the transition path and validates the system's operability. The second approach aims to extend a snapshot model to represent the entire transition pathway. However, they excluded this option due to the lack of models that met the requirements of being fast enough and easily adaptable. Therefore, they developed a new model based on the first methodology, named EPLANoptTP. It uses a multi-objective evolutionary algorithm to optimise the EnergyPLAN model [17]. To manage computational time, the number of decision variables is limited to three: photovoltaic (PV), wind turbine and battery capacities. Thus, the model does not investigate all the options (i.e. criteria (iii)).

This paper presents EnergyScope Pathway, an extension of the open-source and documented EnergyScope TD model [19] listed in Table 1. The latter has an horizon time of one year and does not account for the pathway from an existing energy system to a long-term target. The pathway version extends the time horizon to decades and accounts for the pathway transition from an existing energy system to a long term target. The computational time is kept low (i.e. around a 15 minutes on a personal laptop). In the spirit of the EnergyScope project, the code is fully open-source (under the License Apache 2.0, see repo [43]) with a collaborative documentation [44].

The new model is applied to the case of Belgium, a densely populated country with a limited amount of renewable energies, which represents roughly one third of the forecasted energy demand [45]. This makes it a challenging case to go from a highly fossil-dominated system in 2020 to carbon-neutrality by 2050.

Compared to existing models, EnergyScope Pathway introduces a rapid computational optimization tool for exploring diverse transition pathways within an entire energy system while maintaining high temporal precision to accurately capture the integration of intermittent renewables. To the best of our knowledge, there are potential frameworks that could be extended to similar capabilities, but their computational time for similar case study haven't been find. Furthermore, this paper introduces a linear formulation for extending a snapshot model into a pathway model, while also providing insights into the modeling choices made during methodological development. As such, we aim to contribute to the research community by offering an open-source and well-documented model, along with innovative linear methods for representing investment decisions throughout the transition process.

The paper is structured as follows: in the methodology, EnergyScope TD is briefly presented and then extended into the pathway version (Section 2); then, the case study is presented including the different demands, resources and technologies over the transition (Section 3). Finally, the results section illustrates typical results obtained with the model and compares them with other studies for the energy transition pathway of Belgium (Section 4). Through the paper, a special attention will be kept on the computational time. Two methods will be presented and assessed to reduce the computational burden: a sequential representation of the transition (myopic approach) and a coarser time resolution (monthly).

2 Methodology

EnergyScope TD is a linear programming problem. Extending it to a pathway model while keeping the linear formulation represents several challenges which are (i) the transfer of the energy system design from one year to another, (ii) taking into account society's inertia to change, (iii) accounting for the cost of the transition pathway and the emissions.

The methodology section is structured as follows: first, the snapshot model is introduced. Then, the pathway formulation is presented.

2.1 The starting point: a scenario analysis model

2.1.1 Overview of the snapshot model

EnergyScope TD [19] is a model that optimises both the investment and operating strategy of a '*whole*'-energy system, encompassing electricity, heating, mobility, and non-energy sectors. According to Contino et al. [46], a model qualifies as a 'whole-energy' system when it considers all energy sectors, including the non-energy demand such as the production of plastics and other materials using feedstocks that are also considered as energy carriers, with the same level of detail.

The model's hourly resolution over a year makes it well-suited for integrating intermittent renewables. Its formulation incorporates typical days and a reconstruction method that captures different time scales from the hour to the season while accounting for the inter-weeks patterns of wind. This approach minimally affects the design while significantly reducing computational time [47]. The model investigates all the possibilities by optimising the investment decisions and hourly operations over a year, with a computational time of less than a minute on a personal laptop. This characteristic was intentionally incorporated into the model design to facilitate uncertainty quantification and other studies that require numerous iterations [48].

EnergyScope TD has been successfully applied to various national energy systems, including Switzerland [19, 49], Belgium [45], Italy [50], and other European countries [51]. Furthermore, it has been extended to a multi-region energy system model [47], coupled with other energy models [52], or employed to focus on specific sectors such as the power networks of electricity, gas, and hydrogen [53].

2.1.2 Formulation of the snapshot model

The conceptual structure of the model is illustrated in Figure 2: given the end-use energy demand, the efficiency and cost of energy conversion technologies, the availability and cost of energy resources, the model identifies the optimal investment and hourly operation strategies to meet the demand and minimise the total annual cost or greenhouse gas emissions of the energy system. Typically, the two objectives are integrated by placing a limit on emissions while simultaneously striving to minimize costs.

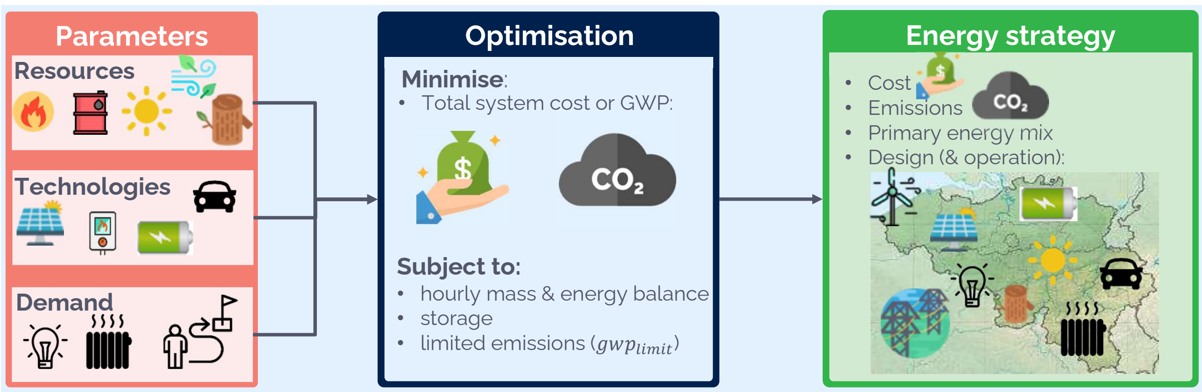

Figure 2: EnergyScope TD model is a flow model with inputs (Parameters), an optimising model (Optimisation) and results (Energy strategy). The image illustrates what is included (non-exhaustively).

2.1.3 Linear formulation

The following section illustrates, non-exhaustively, the original EnergyScope TD model. The objective function, cost and GHG formulation will be detailed. The rest of the formulation is detailed and available in previous works [54]. This paper uses the following nomenclature: SETs are in capital letters, **Variables** are in bold and with first letter capital, and *parameters* are in italic. The formulation results from several developers choices detailed in Appendix B.

$$\min \ \mathbf{C_{tot}} = \sum_{j \in TECH} \Big(\tau(j)\mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j) \Big) + \sum_{i \in RES} \mathbf{C_{op}}(i) \tag{1}$$

$$\text{s.t.} \ \tau(j) = \frac{i_{rate}(i_{rate}+1)^{lifetime(j)}}{(i_{rate}+1)^{lifetime(j)} - 1} \qquad \forall j \in TECH \tag{2}$$

$$\mathbf{C_{inv}}(j) = c_{inv}(j)\mathbf{F}(j) \qquad \forall j \in TECH \tag{3}$$

$$\mathbf{C_{maint}}(j) = c_{maint}(j)\mathbf{F}(j) \qquad \forall j \in TECH \tag{4}$$

$$\mathbf{C_{op}}(i) = \sum_{t \in T} c_{op}(i)\mathbf{F_t}(i,t)t_{op}(t) \qquad \forall i \in RES \tag{5}$$

The objective, Eq. (1), is the minimisation of the total annual cost of the energy system ($\mathbf{C_{tot}}$), defined as the sum of the annualised investment cost of the technologies ($\tau{\cdot}\mathbf{C_{inv}}$), the operating and maintenance costs of the technologies ($\mathbf{C_{maint}}$) and the operating cost of the resources ($\mathbf{C_{op}}$). The annualised factor τ is computed *a priori* based on the interest rate (i_{rate}) and the technology lifetime, (*lifetime*), Eq. (2). The total investment cost ($\mathbf{C_{inv}}$) of each technology results from the multiplication of its specific investment cost (c_{inv}) and its installed capacity ($\mathbf{F}$), see Eq. (3). The installed capacity is defined with respect to the main end-uses output type, such as electricity for PV or heat for a boiler. The total operation and maintenance costs are calculated in the same way, Eq. (4). The total cost of the resources is calculated as the sum of the end-use over different periods multiplied by the period duration (t_{op}) and the specific cost of the resources (c_{op}), Eq. (5). To simplify the reading, we write the sum over typical days as $t \in T$ such as in Eq. (5) and following equations. The period T represents the sequence of hours and typical days over a year (8760h)[2]. The full formulation is detailed in [19] or in the documentation [44].

$$\mathbf{GWP_{tot}} = \sum_{i \in RES} \mathbf{GWP_{op}}(i) \tag{6}$$

$$\mathbf{GWP_{op}}(i) = \sum_{t \in T} gwp_{op}(i)\mathbf{F_t}(i,t)t_{op}(t) \qquad \forall i \in RES \tag{7}$$

The global annual GHG emissions are calculated using a life cycle assessment (LCA) approach, i.e. taking into account emissions of the resources '*from cradle to use*'. It is based on the indicator '*GWP100a-IPCC2013*' developed by the intergovernmental panel for climate change (IPCC) [55]. For climate change, the natural choice as indicator is the global warming potential, expressed in $ktCO_2$-eq./year. In Eq. (6), the total yearly emissions of the system ($\mathbf{GWP_{tot}}$) are defined as the emissions related to resources ($\mathbf{GWP_{op}}$). The total emissions of the resources are the emissions associated to fuels (from cradle to combustion) and imports of electricity (gwp_{op}) multiplied by the period duration (t_{op}), Eq. (7). Thus, this version accounts only for operation without accounting for the global warming potential (GWP) emitted during the construction of the technologies. This makes the results comparable with metrics used in the reports by the European Commission and the International Energy Agency (IEA).

[2]The exception is storage level which is optimised over the 365 days of the year instead of typical days.

The above equations (Eqs. (1) - (7)) represent only a part of the formulation and illustrate the syntax that is used. Those representing the energy balance, network implementation, sectors representation... are not presented in this paper but are detailed in the latest version of the model, see [54] and on the documentation [56]. Energy storage has two dimension to be optimised: the stored energy quantity (also referred to as 'storage level') and the hourly power flow, encompassing both charging and discharging. EnergyScope TD optimises the hourly charge and discharge operations based on the hourly resolution of the typical days. In contrast, the optimisation of stored energy is conducted over the entire span of 8 760 hours in a year. This formulation allows for the effective integration of a wide range of energy storage technologies, spanning short-term solutions like small thermal storage units and daily-use batteries, to longer-term options such as hydro-dam storage for seasonal storage, and even large-scale thermal storage for intra-week patterns. A previous study delved into the roles of various storage technologies, considering their sectoral applications and temporal aspects, within the context of the Swiss energy system [49].

2.2 Extending the model for pathway optimisation

In this section, we delve into the expansion of EnergyScope TD from a static yearly snapshot model to a comprehensive pathway model. While snapshot models provide insights into the energy system for individual years, they lack the capacity to capture the dynamics inherent in investment strategies throughout a transition period. Our proposed approach involves segmenting the transition into five-year intervals, during which the energy system is optimized for one specific year. This approach results in seven instances of EnergyScope TD – called representative years – spanning the 30-year transition period, covering the years from 2020 to 2050. To bridge these representative year, we introduce additional constraints that capture the investments changes between consecutive periods, accounting for societal inertia and evaluating both the cost implications and emissions of the transition. Overall, these constraints are integrated into a linear framework, ensuring computational efficiency, with an approximate computational time of 14 minutes on a personal laptop (2.4 GHz Intel Core i5 quad-core).

Figure 3 illustrates the pathway concept. Simplification and choices were necessary to implement linearly the problem while keeping a tractable computational time. In this section, we present the formulation retained. This formulation results from choices made by the authors detailed in Appendix B, such as the one listed hereafter or the implementation of the efficiency during the transition. Appendix A listes the additional SETS, **V**ariables and *parameters* used for the model.

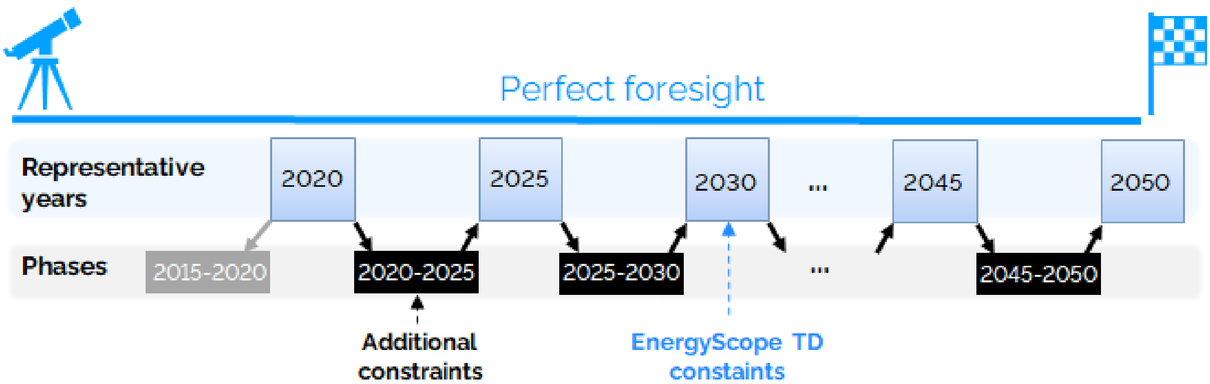

Figure 3: The pathway methodology relies on 7 representative years (blue boxes) where the model EnergyScope Typical Days (EnergyScope TD) is applied. Moreover, the formulation accounts for linking constraints (black boxes) and an initial condition (grey box). The overall problem is the pathway model.

The proposed formulation relies on representative years, selected every 5 years from 2020 to 2050. The period between two of them is called '*PHASE*'. For each of these 7 representative years, the EnergyScope TD model is run using the relevant data (such as energy demand, technology costs or GHG emissions constraints).

As a consequence, a new dimension '*year*' is added to all **Variables** and parameters, except the interest rate (i_{rate}) assumed constant during the transition. This new dimension is necessary to represent the changes of technology and resource characteristics over the representative years. As an example, the investment cost (c_{inv}) of a solar photovoltaic panels could drastically vary in the next decades (e.g. data used ranges between 1220 to 870 [€$_{2015}$/kW] between 2020 and 2035).

2.2.1 Linking years

At this stage, all years are independent. In the following, we introduce new constraints to link representative years. The formulation allows to install new capacity ($\mathbf{F_{new}}$), remove a capacity that has reached its lifespan ($\mathbf{F_{old}}$) or decommission a technology prematurely ($\mathbf{F_{decom}}$). These capacity changes occur during a phase, this implies that there is no capacity change during a representative year. Figure 4 illustrates the concept. This formulation results from choices made by the authors detailed in Appendix B.2.

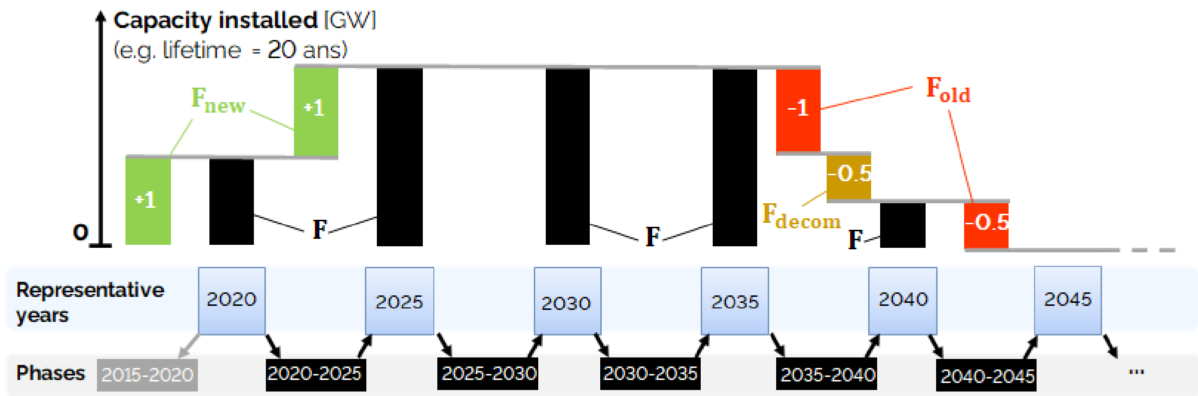

Figure 4: Example of how the technologies capacity and associated variables are evolving. The example uses a technology with a 20 years lifetime. Initially 1 GW of capacity exists ($\mathbf{F_{new}}$ during phase 2015_2020). Then another 1 GW is deployed ($\mathbf{F_{new}}$ during phase 2020_2025). 15 years later, a part of the capacity reaches its lifetime limit and is removed ($\mathbf{F_{old}}$ phase 2035_2040). Moreover, during the latter phase, additional capacity is decommissioned prematurely ($\mathbf{F_{decom}}$). Finally, the technology reaches its expected lifetime and is fully withdrawn ($\mathbf{F_{old}}$).

$$\mathbf{F}(y_{\text{stop}}, i) = \mathbf{F}(y_{\text{start}}, i) + \mathbf{F_{new}}(p, i) - \mathbf{F_{old}}(p, i) - \sum_{p2 \in PHASE \cup \{2015\_2020\}} \mathbf{F_{decom}}(p, p2, i)$$
$$\forall p \in PHASE, y_{stop} \in Y\_STOP(p), y_{start} \in Y\_START(p), i \in TECH \quad (8)$$

Similarly to a mass balance, Eq. (8) is the technology capacity balance. The constraint forces the installation or withdrawing of capacities between two representative years: at the end of the phase (y_{stop}), the available capacity is the one used in the next representative year ($\mathbf{F}(y_{stop})$). This capacity is equal to the one available in the previous representative year ($\mathbf{F}(y_{start})$) plus the new installed capacity ($\mathbf{F_{new}}$) minus the capacity that has reached its lifetime ($\mathbf{F_{old}}$) minus the early decommissioned capacity ($\mathbf{F_{decom}}$). One notices that the capacity available for each representative year depends on a year (y_{start} or y_{stop}), while the other capacity changes depend on a phase (p or $p2$). Moreover, the decommissioning term depends on another phase, which is the one when the technology decommissioned has been built. As an illustration, Figure 4 gives an example where 0.5 GW of a capacity built in 2015_2020 is decommissioned in 2030_2035 ($\mathbf{F_{decom}}$(2030_2035,2015_2020,i)).

$$\mathbf{F_{decom}}(p, p2, i) = 0 \qquad \forall i \in \mathit{TECH}, p \in \mathit{PHASE}, p2 \in \mathit{PHASE} \cup \{2015\_2020\} | decom_{allowed}(p, p2) = 0 \quad (9)$$

$$\mathbf{F_{old}}(p, i) = \text{if}(age = \text{`}\mathit{STILL\_IN\_USE}\text{'}) \text{ then } 0 \text{ else } \left(\mathbf{F_{new}}(age, i) - \sum_{p2 \in PHASE} \mathbf{F_{decom}}(p2, age, i) \right) \qquad \forall p \in PHASE, \forall j \in TECH | age \in AGE(p, j) \quad (10)$$

In linear programming, a solution might be mathematically correct, while not making sense in practice. As an example, a technology could be decommissioned before being built ($p < p_{built}$). Eqs. (9-10) allow to prevent these non-sense while keeping the formulation linear. Eq. (9) forces the decommissioned capacity to zero when technology will be built after. To do so, a parameter ($decom_{allowed}$) is defined *a priori* and is equal to 0 or 1 when decommissioning is not possible or possible, respectively. Eq. (10) defines the capacity reaching its lifetime limit at a certain phase, the concept is illustrated in Figure 4. For each phase, a set (AGE) is calculated *a priori*. It relates, for a given phase and technology, when the technology should have been built. In the case the technology has already reached its lifetime limit, the set (AGE) returns the phase when the technology has been built. The first part of Eq. (10) indicates that the technology is still available, and thus no capacity needs to be removed. The second part of the equation represents the capacity that reached its expected lifetime minus a part of the capacity that would have been decommissioned. As an example, Figure 4 shows a 20 years lifetime technology with 1 GW of capacity installed before 2020. Ones will highlight the use of a 'if' in Eq. (10), this formulation is linear as the if is applied to a parameter and not a variable.

$$\mathbf{F_{new}}(\mathit{2015\_2020}, i) = \mathbf{F}(\mathit{YEAR\_2020}, i) \qquad \forall i \in \mathit{TECH} \quad (11)$$

To initialise the problem in 2020 with the existing design, an additional phase '*2015_2020*' is created. Eq. (11) requires that the capacity used in 2020 is installed in the previous phase (the choice of this initialisation is motivated in Appendix B.1).

2.2.2 Society inertia

To avoid unrealistically fast changes in the system, additional constraints are needed during the phases for the mobility and low temperature heat sectors. Without the following constraints, the model would eliminate certain technologies in one phase, such as oil and gas decentralised boilers. Even if this result is mathematically and physically correct, (i.e. fuels are expensive and investing in more efficient technology is economically and environmentally more profitable), this swap of technology cannot occur in one phase (i.e. 5 years). Indeed, society inertia to change, available manpower, supply chains and manufacturers limit the change.

$$\mathbf{\Delta_{change}}(p, i) \geq \sum_{t \in T} (\mathbf{F_t}(y_{start}, i, t)) - \sum_{t \in T} (\mathbf{F_t}(y_{stop}, i, t)) \qquad \forall j \in \mathit{TECH}, p \in \mathit{PHASE}, y_{start} \in \mathit{Y\_START}(p), y_{stop} \in \mathit{Y\_STOP}(p) \quad (12)$$

$$\sum_{i \in TECH(HeatLowT)} \mathbf{\Delta_{change}}(p,i) \leq lim_{LT,ren} \cdot \big(eui(y_{start}, HotWater) + eui(y_{start}, SpaceHeat)\big)$$
$$\forall p \in PHASE, y_{start} \in Y\_START(p) \qquad (13)$$

$$\sum_{i \in TECH(MobPass)} \mathbf{\Delta_{change}}(p,i) \leq lim_{MobPass} \cdot eui(y_{start}, MobPass))$$
$$\forall p \in PHASE, y_{start} \in Y\_START(p) \qquad (14)$$

$$\sum_{i \in TECH(MobFreight)} \mathbf{\Delta_{change}}(p,i) \leq lim_{MobFreight} \cdot eui(y_{start}, MobFreight)$$
$$\forall p \in PHASE, y_{start} \in Y\_START(p) \qquad (15)$$

Eq. (12) calculates the upper limit of change ($\mathbf{\Delta_{change}}$) in terms of supplied demand instead of installed capacity. Based on this quantification, the amount of change per phase is limited for low temperature heat ($lim_{LT,ren}$), Eq. (13), passenger mobility ($lim_{MobPass}$), Eq. (14) and freight mobility ($lim_{MobFreight}$), Eq. (15). For instance, if the maximum allowable variation in supplied low temperature heat is set at 25%, it would restrict the technology-related changes in low temperature heat to 25% within a given phase. Consequently, if a technology supplies more than 25% of the low temperature heat, it would require multiple phases to replace it with a different technology.

2.2.3 Cost and emissions of the transition

To optimise the energy system, two key metrics must be adapted: the transition cost and the total global warming potential (GWP). Concerning the first one, all costs are expressed in €$_{2015}$ and an annualisation factor is used to distinguish investments over the transition. For the GWP, the metric used is based on the contributions of the gases over 100 years. It is assumed that the impact of emitting at the beginning or the end of transition are equivalent and thus no annualisation is used. This formulation results from choices made by the authors detailed in Appendix B.4.

$$\min \ \mathbf{C_{tot,trans}} = \mathbf{C_{tot,capex}} + \mathbf{C_{tot,opex}} \qquad (16)$$

$$\mathbf{C_{tot,capex}} = \sum_{p \in PHASE \cup \{2015\_2020\}} \mathbf{C_{inv,phase}}(p) - \sum_{i \in TECH} \mathbf{C_{inv,return}}(i) \qquad (17)$$

$$\mathbf{C_{tot,opex}} = \mathbf{C_{opex}}(2020) + t_{phase} \cdot \tau_{phase}(p) \cdot \sum_{p \in PHASE | y_{\text{start}} \in P\_START(p), y_{\text{stop}} \in P\_STOP(p)} \Big(\mathbf{C_{opex}}(y_{\text{start}}) + \mathbf{C_{opex}}(y_{\text{stop}})\Big)/2 \qquad (18)$$

$$\tau_{phase}(p) = 1/(1 + i_{rate})^{diff\_2015\_year(p)} \qquad (19)$$

The objective function to be minimised is the total transition cost of the energy system ($\mathbf{C_{tot,trans}}$), defined as the sum of the total capital expenditure (CAPEX) ($\mathbf{C_{tot,capex}}$) and the operational expenditure (OPEX) ($\mathbf{C_{tot,opex}}$), according to Eq. (16). The total CAPEX ($\mathbf{C_{tot,capex}}$) is the sum of the investment during each phase ($\mathbf{C_{inv,phase}}$), Eq. (17), to which the residual asset investment cost in 2050 is withdrawn ($\mathbf{C_{inv,return}}$). Thus, the investments account for the installation and dismantlement costs of the technologies. The total OPEX ($\mathbf{C_{tot,opex}}$) is the sum of the OPEX in 2020 and the annualised sum of the OPEX during each phase ($\mathbf{C_{opex}}$), Eq. (18). During a phase, the system OPEX is the product of the annualised phase factor, defined in Eq. (19), and the arithmetic average of OPEX cost for the representative years before and after the phase. The annualised phase factor is defined based on an average interest rate during the transition.

$$\mathbf{C_{opex}}(y) = \sum_{i \in TECH} \mathbf{C_{maint}}(y,i) + \sum_{j \in RES} \mathbf{C_{op}}(y,j) \qquad \forall y \in YEARS \quad (20)$$

For each year, the yearly OPEX ($\mathbf{C_{opex}}$) is the sum of the operating and maintenance costs of technologies ($\mathbf{C_{maint}}$) and the operating cost of the resources ($\mathbf{C_{op}}$), Eq. (20).

$$\mathbf{C_{inv,phase}}(p) = \sum_{j \in TECH} \mathbf{F_{new}}(p,j) \cdot \tau_{phase}(p) \cdot (c_{inv}(y_{start},j) + c_{inv}(y_{stop},j))\,/2$$
$$\forall p \in PHASE | y_{\text{start}} \in P\_START(p), y_{\text{stop}} \in P\_STOP(p) \quad (21)$$

The investment during a phase ($\mathbf{C_{inv,phase}}$) results from the multiplication of the newly built technologies ($\mathbf{F_{new}}$) with their annualised arithmetic averaged specific cost, Eq. (21). The annualised phase factor (defined by Eq. (19)) is used. The specific cost during the phase is defined as the average between the investment cost for the first and last year of the period.

$$\mathbf{C_{inv,return}}(i) = \sum_{p \in PHASE \cup \{2015\_2020\} | y_{\text{start}} \in Y\_START(p), y_{\text{stop}} \in Y\_STOP(p)} \tau_{phase}(p) \cdot (c_{inv}(y_{start},i) + c_{inv}(y_{stop},i))\,/2 \cdot$$
$$\frac{remaining\_years(i,p)}{lifetime(y_{\text{start}},i)} \left(\mathbf{F_{new}}(p,i) - \sum_{p2 \in PHASE} \mathbf{F_{decom}}(p2,p,i) \right) \qquad \forall i \in TECH \quad (22)$$

A part of the investment will remain after 2050. This residual investment, also called salvage value, can be calculated for each technology. A parameter, calculated *a priori* , gives for each technology and construction phase, the remaining amount of years (*remaining_years*). As an example, if a PV panel has been built in 2045 and has a 20 years lifetime, the parameter will equal to 15 years. Thus, the salvage value is a fraction of the investment cost of this technology when it has been built. This fraction is the ratio between the number of remaining years and the lifetime of the technology. In the previous example, the residual investment of the PV built is 75%. Eq. (22) computes, for each technology, the residual value that must be deducted from the total cost. The residual value reflects the fact that the technology can still be used after the horizon of the model and is not fully amortised. The residual value is not applied to technologies that are removed prematurely. This differ from other models, such as Plexos where a technology removed prematurely will benefit from its salvage value (see analysis of [30]).

$$\mathbf{GWP_{tot,trans}} = \mathbf{GWP_{tot}}(2020) + t_{phase} \sum_{p \in PHASE | y_{\text{start}} \in Y\_START(p), y_{\text{stop}} \in Y\_STOP(p)} /2\,(\mathbf{GWP_{tot}}(y_{\text{start}}) + \mathbf{GWP_{tot}}(y_{\text{stop}})) \quad (23)$$

$$\mathbf{GWP_{tot,trans}} \leq gwp_{lim,trans} \quad (24)$$

The total global warming potential (GWP) emissions during the transition ($\mathbf{GWP_{tot,trans}}$) are equal to the sum of the total emissions per period ($\mathbf{GWP_{tot}}$), Eq. (23). The emissions during a phase is estimated as the arithmetic average of the representative years before and after the phase. Eq. (24) limits the total GWP emissions during the transition by a maximum ($gwp_{lim,trans}$).

2.3 How to keep a short computational time?

The genesis of the EnergyScope model is the motivation for a short computational time to assess several scenarios and perform uncertainty analyses [57, 58]. The proposed pathway formulation implies a problem size increased by a factor of 7 (i.e. the number of representative years between

2020 and 2050) and a computational time increased by $\sim 7^2$ (typical for linear programming (LP) problems). Thus, performing thousands of runs, sometimes necessary for uncertainty quantification [48, 58], becomes a challenge.

In the following, we propose two methods to reduce the computational overhead. Their performances will be compared in Section 4.2 and put in perspective with the literature. The first method relies on a myopic formulation of the pathway. Instead of optimising at once all the pathway, which implies to have a *perfect foresight*; the myopic version sequentially optimises smaller time windows, in a rolling horizon approach. The second method relies on a coarser resolution of the time: using the monthly resolution instead of the hourly resolution with typical days. This method was originally used by EnergyScope for the case of Switzerland [57]. The implementation of these two approaches are detailed in the following paragraphs.

2.3.1 Myopic resolution

Compared to the perfect foresight, the myopic approach has two main advantages: shorter computational time and more realistic representation of the short-sightedness of decision-makers. For this reason, several studies are based on this approach [59–62]. Babrowski et al. [59] analysed the benefit of the myopic approach to reduce the computational time. Poncelet et al. [60] uses this approach to analyse the expansion planning of the power sector beyond 2050. Nerini, Keppo, and Strachan [61] analysed the impact of the horizon windows and overlapping time. Overall these studies decided to choose the myopic approach to analyse the speed of change compared to a perfect foresight approach. Moreover, the myopic approach allows a sequential optimisation process that opens the doors to decision-making/policy-learning methodologies, like assessing shock events. This approach is used by Heuberger et al. [62] who assessed the speed of integration of technologies due to these events. In their analysis of the overcapacity in European power systems, Moret et al. [63] emphasised that such a "possibility of *recourse*" is very appropriate to address uncertainty gradually unfolding over time. This approach is also taken by Rixhon [64] in a reinforcement learning framework.

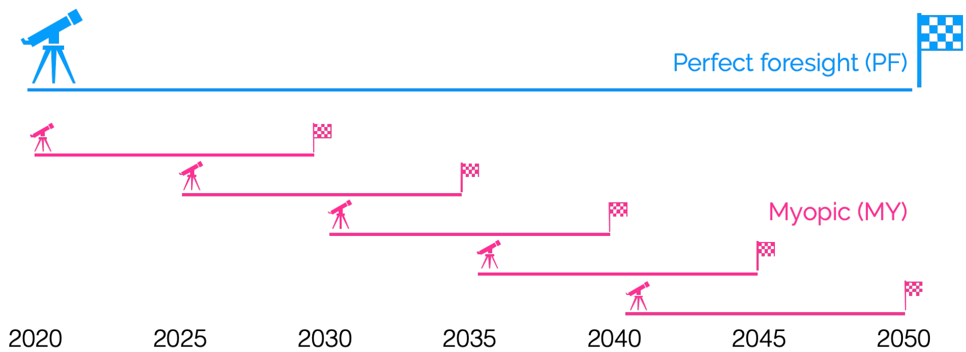

Figure 5: The myopic approach (in pink) uses several instances of the pathway model (illustrated in Figure 3). In this example, the pathway instance has a time horizon of 10 years with a 5 year-overlap. As a comparison the Perfect foresight (in blue) has a time horizon of 30 years.

After optimising, in design and operation, one time window (e.g. from 2020 to 2030), the intermediate system design (i.e. the installed capacities) is set as initial conditions for the start of the next time window (e.g. from 2025 to 2035) as well as the historical investment decisions (i.e. $\mathbf{F_{new}}$, $\mathbf{F_{old}}$ and $\mathbf{F_{decom}}$). Consequently, the solution obtained at the end of the first time window (e.g. 2030) as well as potential investment decisions between the start of the second time window and this end-year are discarded. In other words, they are not taken into account for the optimisation of the second time window. This process goes on until the stated end of the transition (i.e. 2050, in this case).

2.3.2 Monthly time resolution

Originally developed by Moret [57] for the Swiss energy system, the monthly time resolution approach consists in averaging the different time series (e.g. solar and wind capacity factors, varying electricity and heat demands) expressed over the 8760 hours of the year into one value per month. Besides the time resolution itself, the main difference with the typical days/hourly method is the absence of technologies for short-term storage (e.g. lithium batteries, thermal storage in the decentralised heating sector) and constraints related to them.

3 Case study: the Belgian energy system

The proposed formulation can be applied to any regional energy system. In this work, we apply the model to the Belgian case study as data have been collected in previous works [2, 45, 54]. A weakness of the proposed formulation is its one cell spatial resolution. Belgium has a similar weather over the country, the energy networks - mainly gas, oil and electricity - are well deployed and thus using a single cell assumption is reasonable. Belgium is a densely populated country with a limited renewable potential. The Belgian energy mix in 2020 relied on 89.4% of non-renewable resources [65], thus the transition pathway is challenging. Moreover, the Belgian case can represent - to some extent - other industrialised countries highly dependent on fossil fuels.

In this particular case study, a total of 6 demands have been taken into account (refer to Section 3.1), along with 23 resources (see Section 3.2), and 112 technologies (see Section 3.3). In the subsequent analysis, we concentrate on the technologies that have demonstrated significant influence during the transition. For a comprehensive understanding and detailed descriptions of the technologies, please refer to the documentation [44].

3.1 Demands

Demands are characterised by yearly quantities to satisfy (e.g. TWh/y) and hourly time series. The yearly end-use demand (EUD) for all sectors are calculated from the forecast carried out by the European Commission for Belgium (see Appendix 2 in report [66]). An exception to this concerns the non-energy demand since the latter report forecast an unsubstantiated +80% increase compared to the previous edition published in 2016 [67], between 2020 and 2030. Consequently, the values for the non-energy demands come from [67]. Between 2020 and 2050, the commission estimates a linear demand growth of electricity, mobility passenger and freight demands, and non-energy demand. The only exceptions are high and low temperature heats which have a reduction of 3.3% and 10.2%, respectively. Figure 6 illustrates the end-use demand (EUD) implemented. For the time series, they are used to assess the operability of the system by optimising the hourly dispatch over the typical days. These time series are based on historical values of 2015 for electricity and space heating. A daily time series is used for the passenger mobility. The other time series are assumed constant over the year.

The demands can be regrouped in four energy types: electricity, heat, mobility and non-energy. Heat is split in three different sectors: high temperature heat (or industrial heat) for processes, low temperature heat that can be supplied by a centralised system (i.e. DHN) and low-temperature heat that must be produced in a decentralised way. Mobility is split in three types: freight, public passenger and private passenger. The non-energy demand is usually omitted in simulations despite being 10% of the energy consumption worldwide [68]. In the

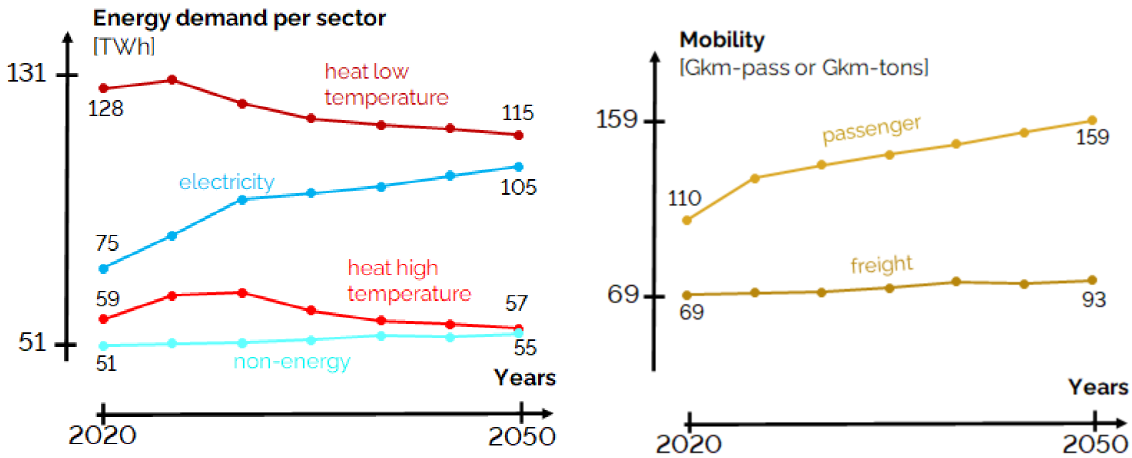

Figure 6: The six types of yearly end-use demands can be regrouped into two categories. The ones that can be expressed in energy (TWh) and the ones that are expressed in mobility (kilometers). The non-energy demand is expressed in tons of feedstocks translated into TWh based on the methodology proposed by [2].

case of Belgium, this sector represents 20% of the energy consumption. Examples are chemicals (e.g. plastics, fertilisers...) or raw materials (e.g. bitumen). Based on the work of Rixhon et al. [2], this sector has been implemented in this study by accounting for three demands: methanol, ammonia and high value chemicals (HVC). These three products cover 90% of the total non-energy demand worldwide [68] and 91.6% in Belgium in 2015 [69]. HVC "gathers light olefins (e.g. ethylene, propylene) and aromatics (i.e. benzene, toluene, and xylene (BTX)), mainly used in the production of plastics, synthetic fibers, or rubber". Methanol "is mainly converted to formaldehyde (i.e. resin), but is also used for the production of other chemicals" and ammonia "is mainly used for the production of fertilizers, which cover more than 80% of its use." [2].

3.2 Resources

Resources can be regrouped into two categories: endogenous and exogenous. In the case of Belgium, endogenous resources are mostly renewable: solar, biomass, wind and hydro. The only endogenous resource which is non renewable is waste. The renewable potential is limited by the availability of lands, either limiting the energy available (in TWh/y), such as biomass; or the technology deployment (in GW), such as solar, wind and water based technologies[3]. In a previous work [45], the potentials have been reviewed and estimated to 60 GW of Photovoltaic (equivalent to 61.7 TWh/y), 10 GW of Wind onshore (equivalent to 21.3 TWh), 0.38 GW of hydro run-of-river (equivalent to 1.6 TWh), 23.4 TWh/y of biomass, 38.9 TWh/y of digestable biomass. The offshore wind potential has been revised due to additional concession in the sea. The potential is now estimated to 6 GW (equivalent to 21.6 TWh). The overall renewable potential is equivalent to ≈170 TWh/y available plus 17.8 TWh/y of non-renewable waste.

Exogeneous resources account for fossil fuels, which are prevailing today's energy system. Additionally exogeneous resources account for electrofuels, which rely on renewable electricity as defined in [70], are also permitted. Furthermore, the importation of electricity from neighboring countries is allowed, subject to an additional constraint that accounts for grid interconnection and simultaneity factors. The latter factor represents the maximum capacity for importing electricity from all neighboring countries. The Belgian transmission system operator (TSO)

[3]Regarding the latter, it should be noted that the upper bound will be constrained by the technology capacity rather than the availability of resources.

has historically reported this factor to be approximately 66% [71]. According to the TSO [72], the interconnection capacity is expected to gradually increase to 18.1 GW by 2050, with a simultaneous capacity of 11.9 GW. The latter value is implemented.

Resources are characterised by a price [€/TWh], an availability [TWh/y] and a GHG intensity [$ktCO_{2,eq}$/TWh]; the latter based on a LCA (see details in the documentation [44]). Availability and GHG intensity are constant over the transition except for electricity imported. The value of the imported electricity GHG in 2020 is derived from the European mix (413.0kgCO2-eq/MWh), while the value in 2050 is 0. In between, the GHG intensity is interpolated linearly. The resources prices are summarised for the different years in Table 2, data are based on [73] forecast for fossil fuels and electricity; while [74] estimates the costs for electrofuels. The electricity import availability is limited to 30% of Belgium electricity EUD to limit dependency from neighbouring countries. This arbitrary availability is three times greater than historical values in the last two decades [75].

Table 2: Fuel prices ($€_{2015}$/MWh) in years 2020 and 2050 for different resources. Except for biomass, all resources are imported. Upper part of the Table shows fossil resources and their equivalent renewable substitutes. Lower part of the Table shows the remaining resources. The prices are assumed to change linearly during the period 2015-2050. Abbreviations: light fuel oil (LFO).

Non-renewable ($€_{2015}$/MWh)			**Renewable** ($€_{2015}$/MWh)		
Year	**2020**	**2050**		**2020**	**2050**
Gasoline	66	94	Bio-gasoline	123	100
Diesel	63	91	Bio-diesel	131	109
LFO	48	69	-		
Fossil gas	34	53	e-methane	132	104
Ammonia	72	114	e-ammonia	93	71
Methanol	81	116	e-methanol	123	100
Hydrogen	78	96	e-hydrogen	138	101
Coal	16	18	Woody biomass	30	36
Waste	21	25	Wet biomass	5	6
Uranium	4	4	-		
Imported electricity[a]	57	105			

[a]It is assumed that carbon footprint of the imported electricity decreases from the European mix historical value in 2015 (413 $kgCO_{2,eq}$/MWh) until net zero by 2050. Price is based on historical values and increased by a factor 1.36 until 2035.

3.3 Technologies

Technologies are characterised by an investment cost [M€/GW], an operating cost [M€/y/GW, a conversion efficiency (if applicable), a GHG emission for the construction [$ktCO_{2,eq}$/GW], a lifetime [years], a maximum capacity factor (if applicable) and a minimum and maximum deployment [GW]. The previous units were expressed for power supply technology (in GW). This unit changes to GWh for storage technologies, Mpkm/h for passenger technologies and Mtkm/h for freight technologies.

The technologies account for three sub-groups: conversion technologies, storage technologies and infrastructures. Conversion technologies are characterised by conversion efficiencies as it converts resources into other energy carriers, such as a PV panel that converts solar irradiance into electricity, or a gasoline car that converts gasoline into kilometer passenger or even a synthetic methanolation plant converting captured CO_2, hydrogen and electricity into methanol and low-temperature heat. Storage technologies are characterised by charging/discharging efficiencies [%], internal losses [%/h] and an energy-to-power ratio [h]. Infrastructures encompass the electrical and DHN grids. They are characterised by a size, an investment cost and a lifetime. For the power grid, the size is proportional to the deployment of intermittent renewable (367.8 M€/GW, see [54] for details). For the DHN, the size is proportional to the DHN heat production capacity and is estimated at 825M€/GW_{th}.

The investment and maintenance costs as well as the efficiencies are evolving over the years, especially for promising technologies such as batteries or electrolysers. These data come from the Danish energy agency database that regularly updates the techno-economic specifications of most of the implemented technologies [76–78]. In its previous version (see [54]), the consistency of the data for the electricity and mobility sectors have been verified with a literature review of two metrics: levelised cost of energy (LCOE) and the total cost of ownership (TCO). Since then, the forecast for vehicles prices have been revised based on more recent literature [66, 79]. The resulting updates are more efficient battery electric vehicle (BEV) and more expensive fuel cell (FC) cars, that make the former more competitive.

3.4 Society inertia and political framework

The inclusion of additional constraints becomes necessary to prevent excessively rapid changes in the sectors mentioned below. In the case of the mobility sectors ($lim_{MobFreight}$ and $lim_{MobPass}$), a value of 50% has been selected to represent a transition period of 10 years, which corresponds to the average lifespan of private cars. For the heating sector ($lim_{LT,ren}$), a value of 33% has been adopted to signify a transition period of 15 years. These values reflect ambitious targets and entail significant societal changes. The reasoning behind these choices is to allow for rapid system transformations without excessively restricting the system. As an illustration, heat pumps are a promising technology to decarbonise the heat sectors but its supply chain is not yet on track to meet its massive penetration [80].

The green deal, a legislation from the European Union is directing Belgium to reach carbon neutrality by 2050 [81]. This directive is translated into a upper bound for the yearly GHG for the system and for each representative year. The bound is set arbitrary as a linear decrease from 2020 value to 0 in 2050. Implementing the GHG target into yearly constraints is necessary for the myopic approach. Indeed, it doesn't optimise the full transition at once and needs a constrain. An alternative formulation, not comatible for the myopic, is to define a carbon budget as stated in Equation 24. A study with this formulation is available in a previous work [54].

All the numerical value and details of the sources and pre-processing have been detailed in [54] and are updated in the collaborative documentation [44].

3.5 Hourly time series

The models necessitate hourly time series to allocate annual demands or potential into hour-by-hour profiles. Two key characteristics of these time series are of paramount importance: their hourly amplitudes and their hourly correlations with other time-related data sets. For instance, an anti-correlation exists between heat demand (mostly in winter) and solar energy (mostly in summer). Accounting for these two parameters are key to ensure a consistent hourly profiles.

To maintain the correlations among these time series, historical data spanning the year 2015 have been used to create dimensionless time series. These time series can be categorised into two groups: demand and technology. Within the demand category, we have implemented hourly profiles for electricity demand, space heating demand, and passenger mobility demand. For the latter, we used a daily profile repeated throughout the year without distinction between weekdays, weekend-days and holidays. The other demand, which are domestic hot water, industrial heating, freight mobility, and non-energy demand per feedstocks, the demand was assumed constant over time.

Some technologies weather dependent uses a time series to constraint their production. This formulation comes on top of a yearly capacity factors. These technologies include solar photovoltaic, solar thermal, hydro-dams, hydro-rivers, onshore wind turbines, and offshore wind turbines. Belgium's renewable energy production predominantly relies on solar PV, onshore, and offshore wind turbines. The time series for these technologies are derived from historical production data available from the TSO. For thermal solar, historical irradiance data for 2015 were used. For hydro rivers, it plays an almost negligeable role in the Belgian electricity mix and thus we used swiss data. Detailed hourly time series data are accessible in the data section of the documentation [56] for further reference and analysis.

4 Results

The following sections show the results of the model applied to the case study. In the first section, the perfect foresight model is applied and typical results are illustrated. In the second section, a comparison is performed between the perfect foresight, the myopic and the monthly versions.

4.1 Belgian energy transition pathway

In the following, we first perform a technical investigation of the pathway by checking the greenhouse gas breakdown by energy sectors and then the primary energy mix is analysed. To illustrate the sector coupling, a focus is made on the electrification of other sectors. Then, the cost implications in terms of investments and operations are discussed.

4.1.1 Greenhouse gases and primary energy

Figure 7 shows the greenhouse gas (GHG) per sector. As a reminder, the total GHG is capped linearly between its historical value in 2020 (121 $MtCO_{2,eq}$) and 0 in 2050. This approach is necessary for the myopic approach, while other approaches, such as imposing a carbon budget over the transition or an end goal (carbon neutrality in 2050) would be more realistic[4]. The system reaches its upper bound (i.e. maximum emissions) every year.

The defossilisation[5] of the different sectors are not performed at the same rate. The non-energy demand of methanol and ammonia are substituted by electrofuels. These are the first use of electrofuels as e-ammonia is the cheapest electrofuel thanks to the high maturity of the haber-bosch process. The decentralised heat and mobility sectors are also dropping first. This is a combination of efficiency and substitution of fossil fuels with electricity. Efficiency comes mainly from district heating networks and electrical heat pumps for the heat sector, and public

[4]The carbon budget has been implemented for the perfect foresight in a previous work [54]. In this work, Figure 7.14 shows a Pareto Carbon-budget - transition cost. The study shows that no transition would be 7% less expensive but emitting 75% more GHG while not achieving carbon neutrality. Moreover, reducing the carbon budget by a little amount could have a small impact on the cost down to a certain amount. As an example, reducing the carbon budget by 13% will imply an extra cost of 1.3%.

[5]In a more sustainable future, some of the energy carriers, currently produced mostly from fossil resources, will still consist of hydrocarbons (e.g. e-methane or e-methanol). This is why this paper rather uses "defossilisation" rather than "decarbonisation" as carbon will still play a key role in a carbon-neutral energy transition [82].

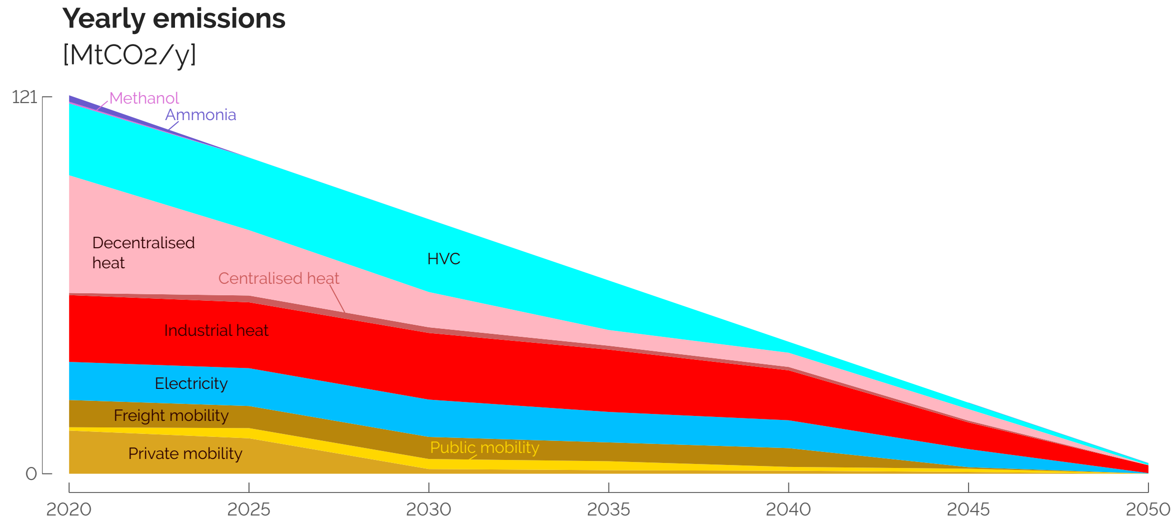

Figure 7: Energy sectors have different speed to reduce GHG emissions over the transition. The system uses all the allowed GHG prescribed by the linear decrease from the emissions in 2020 until carbon-neutrality in 2050.

mobility and electric cars for the mobility sector. From 2040 onward, the decreases are mainly due to the substitution of the remaining fossil fuels by electrofuels as illustrated in Figure 8.

Figure 8 shows the primary energy mix for the different representative years. The pathway verifies five trends: (i) reduction of primary energy thanks to energy efficiency; (ii) massive integration of endogenous renewable energies; (iii) importance of electrification; (iv) the usage of gas as the last fossil resource; and (v) the obligation to rely on renewable fuels to achieve carbon neutrality.

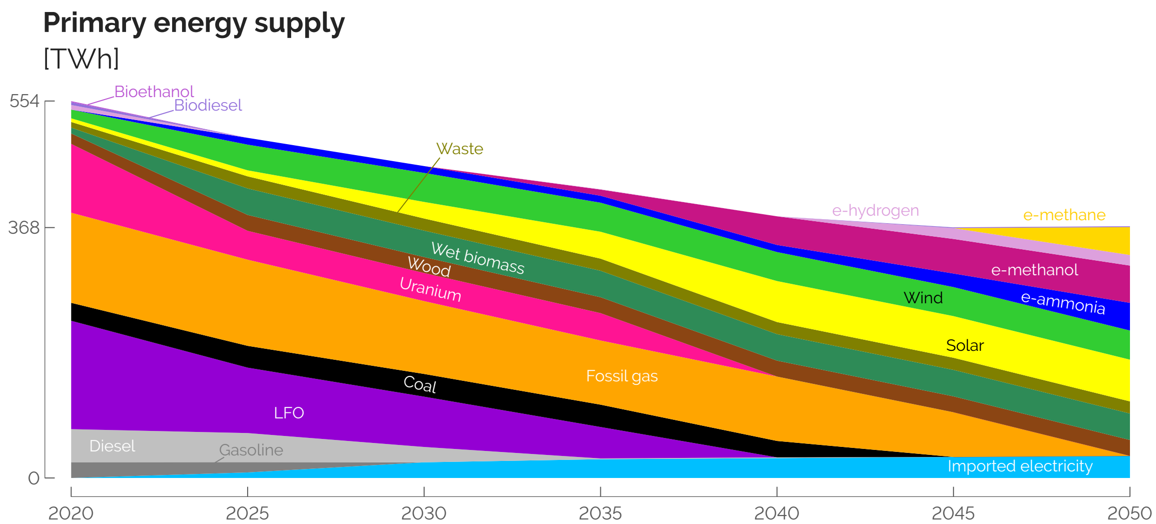

Figure 8: Primary energy emitting GHG (below Uranium) are reducing linearly with fossil gas remaining until 2045. A part of this energy is replaced by renewable ones and starting from 2040, a significant share of electrofuels. As end-use demands slightly increase (see Figure 6), the drop represents energy efficiency (i.e. providing the same services with less primary energy). Abbreviations: light fuel oil (LFO) and e-*molecule* stands for a renewable molecule with no global warming potential.

The energy supply decreases from 554 TWh/y in 2020 down to 368 TWh/y in 2050 (i.e.

-34%) whereas, in the meantime, the demands have increased by 19%, on average. This drop of primary energy consumption reflects the penetration of efficient measures and technologies, such as the previously mentioned public mobility, DHN or heat pumps. The results in 2050 are aligned with other studies, such as Devogelaer et al. [83][6] and My2050[7] [85] which estimates respectively a range of 305-417 TWh/y and 307-364 TWh/y for their central scenarios.

The first fossil energy to phase out is gasoline, which is exclusively used for private cars. Indeed, private mobility is partially replaced by public one[8]; and the cars are switching from gasoline and diesel to electricity. Then, diesel and LFO are decreasing. As diesel is used for trucks and buses mobility, it is harder to phase out compared to gasoline exclusively burned in cars. The first drop of LFO reflects the switch from oil boilers to other technologies: heat pumps and gas cogeneration mainly. Then, it is mainly used for the production of HVC, this reflects that HVC is a feedstock hard to defossilise. Finally, coal is kept mainly for industrial usage because it is a cheap fossil fuel (mainly for industrial usage). To phase it out beforehand, a penalty mechanism, such as a carbon tax, would be required, or its strict ban should be put in place. The last fossil energy present in the system is fossil gas, used for the production of electricity and heat, through cogeneration mainly. Indeed, gas plays a key role to balance the intermittency of solar and wind.

The consumption of uranium declines in 2025, dropping to 2 GW, primarily due to the political framework aimed at phasing out nuclear energy [87]. In the initial stages, significant deployment of endogenous energies takes place. This includes the utilization of wood, wet biomass, and wind energy, followed by the introduction of solar energy. However, solar energy is not fully deployed during this period due to higher integration costs. Starting from 2025, the importation of electrofuels begins, although their significant utilisation is observed from 2035 onwards. Initially, these fuels are predominantly employed as feedstocks in non-energy sectors. From 2040, e-methanol is additionally utilised for the production of High-Value Chemicals (HVCs), e-hydrogen is employed for mobility purposes, and both e-methane and e-ammonia are used for electricity generation through gas combined heat and power (CHP) and ammonia-based combined cycle gas turbine (CCGT) plants (see Figure 9).

In 2020, Belgium has been a net-exporter of electricity, however with the shut-down of nuclear power plants and the increase of electricity consumption, Belgium will become a net importer of electricity. These imports reach their maximal allowed capacity by 2035 (i.e. 30% of electricity end use). This strong dependence on imported electricity illustrates the need for balancing intermittent renewables without relying on fossil fuels.

4.1.2 Electricity sector: Capacities and yearly balance

To better understand the electricity sector, the installed production capacities are given in Figure 9, while the supply-demand yearly balance is illustrated in Figure 10.

As introduced in the primary energy analysis (see Figure 8), renewable capacities soar. By 2050, wind and solar technologies deployments are 60 GW of PV, 10 GW of onshore wind turbines and 6 GW of offshore wind turbines. To compensate the intermittency, the system relies on imported electricity, gas CCGT, sector coupling and storage. As an illustration, in 2050,

[6]This study was ordered by the National Planning Bureau in 2013. Five scenarios are proposed.

[7]The Climate Change Service of the Federal Public Service Health launched an initiative in 2012 entitled '*Low Carbon Belgium by 2050*'. This initiative resulted in a report and a calculator in 2013 [84]. The Belgian calculator has been improved since then into a recent expert version called **My2050** [85]. From this study, the results of two scenarios will be used: one based on an optimistic evolution of technologies (Technology), and one focusing on an increased dependence on neighbouring countries (EU integration).

[8]Given the major role played by private cars in the Belgian passenger mobility nowadays (i.e. around 80% [86]), public transport (e.g. tramways, buses and trains) is assumed to be able to supply only half of it.

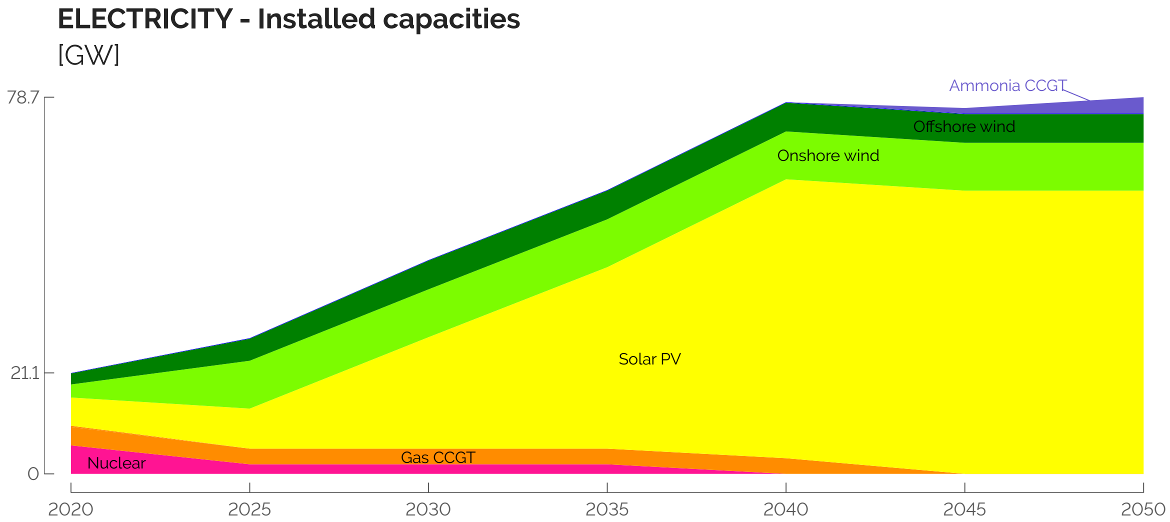

Figure 9: The electrical production capacity will experience massive expansion of wind turbines (onshore and then offshore) and a soaring installed capacity of PV. Ammonia CCGT are installed at the end of the transition to provide a flexible capacity as gas CCGT are phased out. Abbreviations: combined cycle gas turbine (CCGT) and photovoltaic (PV).

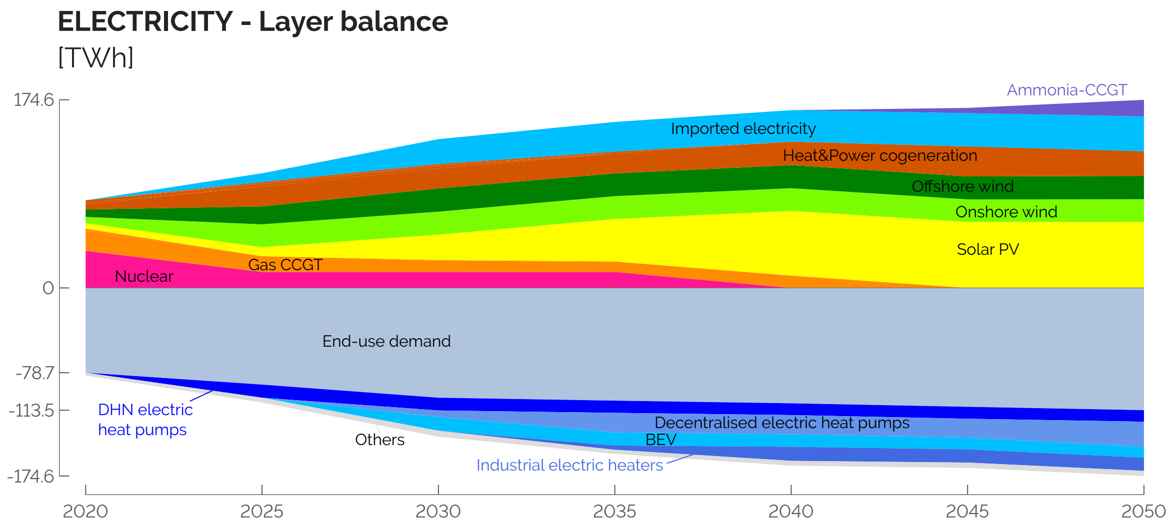

Figure 10: The electricity supply (positive values) will remain a mix of different technologies where backup is first mainly provided by gas-CCGT and then imported electricity, heat and power cogeneration and later ammonia-CCGT. The electricity demand (negative values) is led by the electricity end-use demand, but the share used to electrify heat (heat pumps), vehicles (cars, trains, trams, ...) and industrial heaters drastically increase. This enables a flexible demand that can facilitate the integration of intermittent renewables. Abbreviations: battery electric vehicle (BEV), Combined cycle gas turbine (CCGT), district heating network (DHN) and photovoltaic (PV).

176.8 TWh of electricity transit on the grid which includes 32.4 TWh of electricity imported and 15.4 TWh of electricity from CCGTs. This result is aligned with other studies that estimates different ranges: 180-310 TWh/y [83], 126-140 TWh/y [85] and in a more recent study using the TIMES-BE model, 185-196 TWh/y [88]. Higher values from Devogelaer et al. [83] illustrate an almost exclusively electrified energy system. The differences between the study ranges reflect the different assumptions in term of renewable potential and availability of nuclear energy. A general trend is that Belgium should maximise its use of endogenous renewable resources, which Dubois et al. [89] identified as a cheaper option than importing additional renewable energies from abroad. Demand management reflects the flexible use of electricity, mainly through heat pumps that uncouple the heat demand and the electricity consumption when combined with thermal storage. Gas CCGT is also a useful asset to compensate intermittent renewables. However, its capacity remains the same as the one installed in 2020. These results are verifying an hourly adequacy of the power demand. Moreover, in a previous study by Pavičević et al. [52], the snapshot version of the model has been coupled with Dispa-SET, a dispatch optimisation model. Results showed that the backup capacity was underestimated by less than 20% to respect reserve capacity, mainly due the lack of reserve capacity for grid stability.

From 2025, the electricity mix has a strong renewable share that rises up to 60% in 2050. The remaining 40% are mainly gas (or ammonia) in CCGT and cogeneration and imported electricity. From a demand perspective, the electrification first starts with DHN heat pumps, then electric cars, then decentralised heat pumps and finally industrial heaters. The latter reflects the usage of cheap PV production peaks.

4.1.3 Costs: Investments and operation

In the following paragraphs, the results are analysed from an economic perspective to decipher the choices made by the model, as the overall cost of the transition is 1 004 b€$_{2015}$ split unequally among the sectors.

Figure 11 illustrates the cumulative investments made throughout the transition, amounting to a total of 377.8 b€$_{2015}$. Initially, the infrastructure, transport, and electricity sectors each account for approximately one-third of the investments. The investments in infrastructure are primarily driven by the electricity grid and the district heating network (DHN), representing a combined investment of 73 b€$_{2015}$. The electricity sector's investment is led by power plants, totaling 31.5 b€. Notably, the investment costs in the mobility sector are primarily attributed to private cars, constituting 71% of the total. A rough estimation confirms the significant investment in cars, with an average of 500,000 vehicles registered annually in Belgium over the last decade [90] and assuming an average cost of 20 k€ per car, the funds allocated to private cars amount to 10 b€ per year. This trend in private cars explains why the private mobility sector accounts for half of the investments required to achieve the transition by 2050. This finding aligns with other studies, such as Devogelaer et al. [83], which estimates cumulative investment expenditures of approximately 600 b€$_{2005}$ for the transport sector between 2013 and 2050, which confirms our conservative approach in the estimation.

As a comparison, the investments required to fully deploy the PV and wind potentials from 2020 to 2050 amount to 74.4 b€$_{2015}$, with an additional 22.2 b€$_{2015}$ allocated to reinforce the grid. The electrification of the heating sectors necessitates investments of 29.2 b€$_{2015}$, including 6.5 b€$_{2015}$ for the deployment of the DHN infrastructure. Storage investments, primarily focused on DHN seasonal storage, amount to 3.6 b€$_{2015}$. Apart from the investment required to replace all private vehicles (accounting for 44% of the overall investments), the remaining sectors represent a total of 212 b€$_{2015}$. To mitigate the cost of the transition, My2050 suggests deploying a fleet of no more than one million vehicles and implementing a car sharing system, distinct from car-pooling, as an inevitable measure [85].

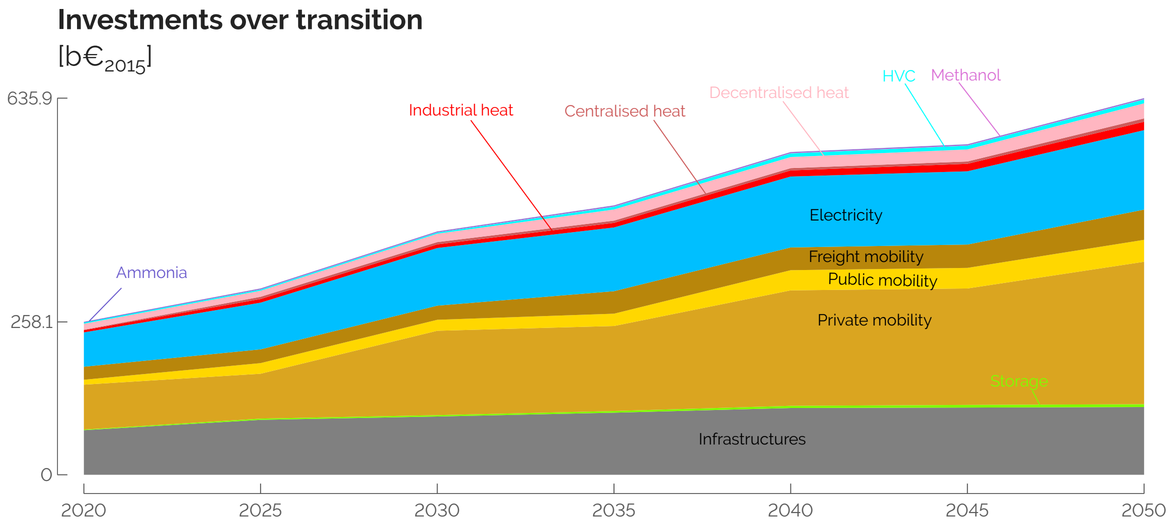

Figure 11: The cumulative investments over the transition is unequally spread between the sectors. The energy system in 2020 is imposed to the existing energy system and its expenses are split in three main categories: mobility (mainly vehicles), infrastructure (mainly grids) and electricity (mainly thermal power plants). The investments required during the transition represents 150% the initial investment and mainly in the same three sectors. Abbreviation: high value chemicals (HVC).

A part of the investment will be recovered at the end of the transition based on the remaining lifespan of the technology after 2050. Figure 12 illustrates the salvage value by sectors, calculated according to Eq. (22). Out of the 114.4 b€$_{2015}$ of investments, in the infrastructure (i.e. mostly power grid and gas network), 55.9% remain available after 2050, due to their long lifetime. On the contrary, private mobility has a lower salvage value due to a major drop within the first four years and an average lifetime below 10 years [90].

In addition to investment decisions, the operational expenditure (OPEX), which account for resource utilisation and technology maintenance, are significant. Figure 13 shows the yearly system cost for each sector except the OPEX related to resources that are grouped together. The latter dominate the OPEX, with a significant share of non-renewable resources (e.g., 63.6% in 2020) until 2040, followed by a steep increase in the share of renewable resources (e.g., 66.2% in 2050). The substantial reliance on non-renewable resources reflects the prevalent use of fossil fuels in our current energy system. The high cost-share of non-renewable fuels underscores the economic challenges of simply substituting fossil fuels with renewables, particularly evident when emphasing that electrofuels are 2-3 times more expensive. Maintenance expenses in the private mobility sector rank second in terms of expenditure. On the other hand, maintenance expenses in other sectors are relatively small compared to the aforementioned sectors.

The annualised cost of the energy system in 2015 is estimated to 44.3 b€/y and increases by 5.5 b€/y to reach 49.8 b€/y by 2050. **My2050** estimates the annualised cost in 2050 between 63 and 82 b€/y, while the other studies just indicate the cost increase compared to 2015 (+11.7 to +21) [83, 88]. The differences come from the scope of the energy system, as an example **My2050** also accounts for the agriculture sector. These differences highlight the difficulty to compare different studies due to difference of scope and partial availability of data used. Overall, comparing with existing study show the consistency of the results provided by EnergyScope Pathway.

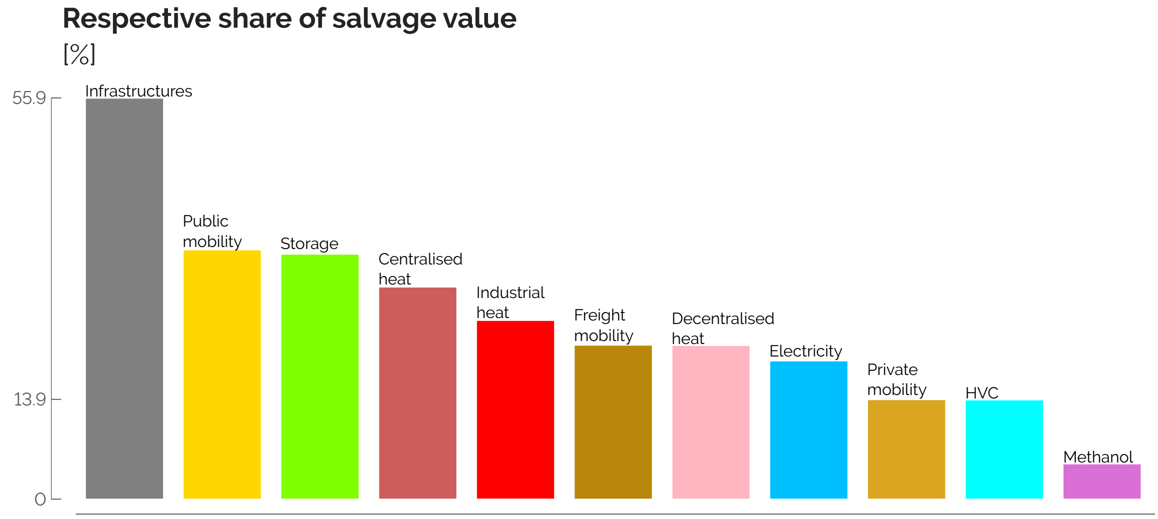

Figure 12: By the end of the transition (i.e. in 2050), the ratio between the salvage value and its cumulative investment, per sector, is unequal. Investments in infrastructures, public mobility, storage and other long-lifetime technologies experience an important salvage value, at the contrary, investments in private mobility will not be recovered as vehicles have a short lifetime. All together, these salvage values represent 160.1 b€$_{2015}$, 25% of the cumulative investment costs in 2050.

4.2 Reducing computational time

The EnergyScope models have the advantage of a concise formulation and short computational time. By extending it to the transition pathway, the computational cost soars from 34 seconds to 14 minutes (on a personal laptop). Two methods have been introduced in the methodology (see Section 2) to reduce the computational time: the myopic approach (**MY**), and the monthly resolution (**MO**).

Where Appendix C presents a more exhaustive comparative analysis between the different approaches, the current section aims at exploring the main distinctions pointed out in Table 3.

4.2.1 Myopic versus Perfect foresight

As expected, the computational time is reduced by 55% while the design remains similar. Given the continuous change of the input parameters over the considered time frame, the perfect foresight and myopic approaches results are very similar, like in [91]: less than 1% cost difference over the transition, similar system designs by 2050 and slight shifts in time in terms of adoption of technologies. A more detailed comparison is available in Appendix C.

The main difference lies in the transition itself and especially in the earlier deployment of PVs and offshore wind turbines. These induce the reinforcement of the grid that is capital-intensive and long-lifetime asset. This is mostly due to the chosen formulation of the salvage value. Since the objective function is now the transition cost over a more limited time window (i.e. 10 years rather than 30 years), a bigger salvage value, deduced from the total investments, leads to a temporary better optimum at early stages of the transition.

4.2.2 Monthly versus Hourly

As expected, the computational time drops by 99%. The total transition cost is similar (≈2%). However, the design of the system is different, see Table 3. Beyond the technologies not captured which are daily storage technologies, intermittent renewables (PVs and wind turbines) are much

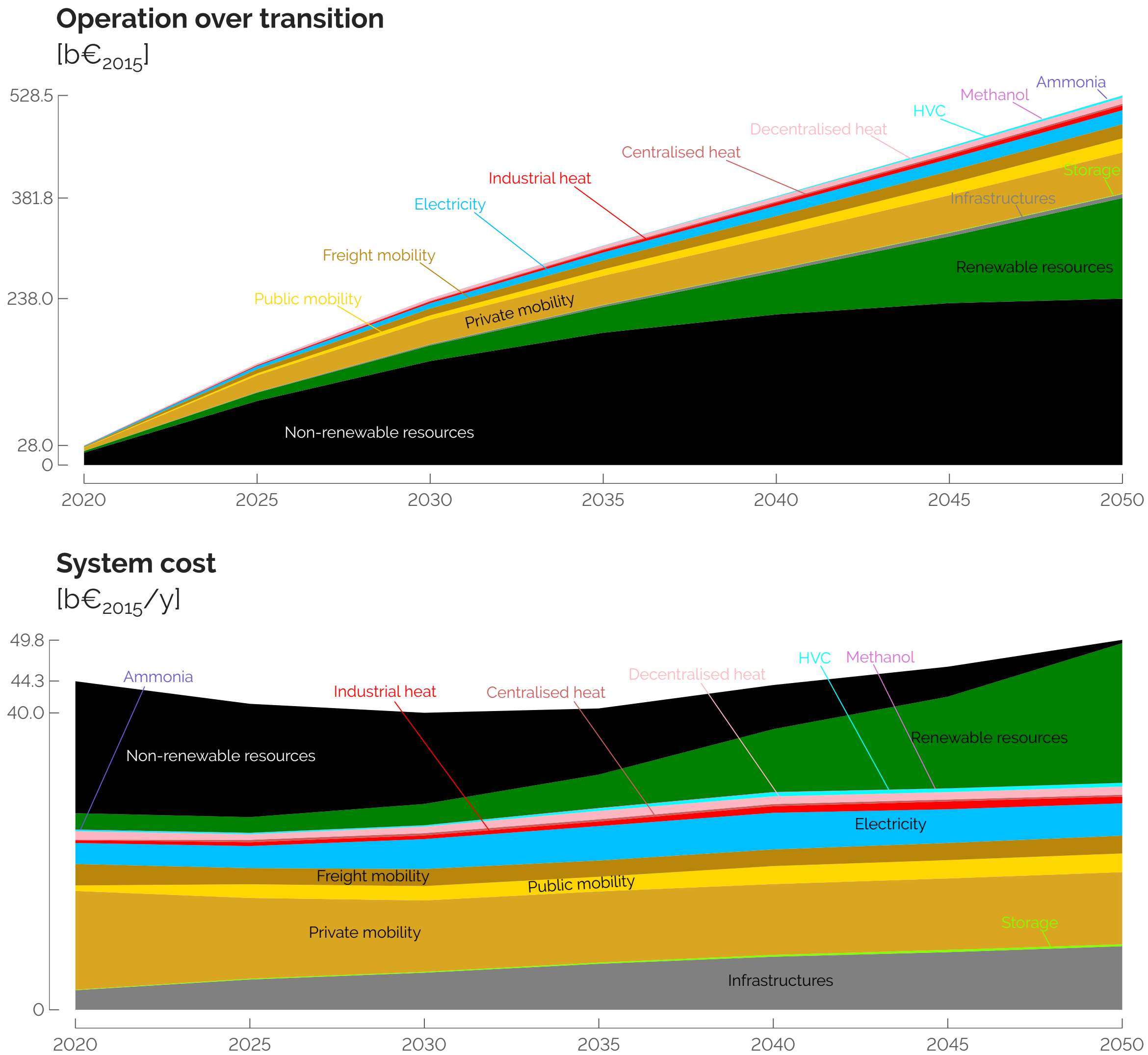

Figure 13: The yearly system cost shows the shift from non-renewable to renewable resources (mainly electrofuels). Operation cost and maintenance represents almost 50% of the expenses.

Table 3: Summarised general differences between the three approaches: Perfect foresight with hourly resolution (PF), Myopic with hourly resolution (MY), and Perfect foresight with monthly resolution (MO). Differences with the reference case (PF) below 1% are not shown ($\simeq$), and ones above 10% are in bold.

		PF	**MY**	**MO**	Units
Computational time[a]		830	**373**	**2**	s
Transition cost by 2050		1004	$\simeq$	-2%	b€$_{2015}$
Primary energy mix in 2050	Total	368.0	$\simeq$	+2%	TWh/y
	e-methane	41.0	+6%	**+51%**	TWh/y
	e-ammonia	40.7	-10%	**+55%**	TWh/y
Electrification in 2050[b]	System[c]	63.3	$\simeq$	**-27%**	TWh$_e$
	Industrial heat[d]	12.3	-7%	**-98%**	TWh$_{th}$
	Decentralised heat[d]	73.9	$\simeq$	**-13%**	TWh$_{th}$
Year of full VRES-deployment	PV	2045	**2040**	**2040**	-
	Wind-offshore	2030	**2025**	**2025**	-
	Wind-onshore	2025	2025	2025	-

[a]These computational times were reached on a 2.4GHz 4-core machine.

[b]The electrification of the other sectors (i.e. centralised heat (100%-heat pump), private (100%-BEV), public mobility (80%-train and tramway), freight mobility (25%-train) and non-energy demand (0%)) are identical between the three approaches and are, therefore, not presented in the table.

[c]The electrification of the system is computed as the difference between the total production of electricity and the end-use demand of electricity.

[d]The electrification of the industrial and decentralised heating sectors is expressed in terms of thermal energy (TWh$_{th}$) provided by electrified processes, respectively industrial resistors and decentralised electric heat pumps.

easier to integrate in the system as the daily supply-demand intermittency and mismatch are not at stake. This explains why industrial resistors, and decentralised electrical heat pumps to a smaller extent, are barely installed in the monthly approach whereas they are used to absorb the renewable electricity produced by PVs during the sunny days, in a carbon-neutral 2050, in the hourly model.

Consequently, this leaves the industrial and decentralised heating sectors relying more on conventional technologies, boilers and heat pumps, but running on renewable e-methane. Finally, to respect the limit on emissions, the model decides to invest earlier (i.e. 2045) in more CCGT running on e-ammonia, rather than importing electricity from abroad. This explains the increase of e-ammonia consumption in 2050. A more detailed comparison is available in Appendix C.

In conclusion, both monthly and myopic alternatives reduce the computational time. Although, the monthly alternative is inaccurate to capture the integration of intermittent renewable energies. However, its very short computational time makes it ideal to perform thousands of runs and can be used to some extends. The myopic appears as an accurate alternative that might slightly over-invest. Similar trends have been reached in a similar study where GHG weren't constrained, see details in Appendix C.3

5 Conclusions

In the urgency to address the climate crisis, the objective to reach carbon-neutrality by 2050 has been clearly set worldwide [92]. However, the ways to get there are numerous [93] and trigger debates. To feed these discussions and give more insight to decision makers, we have developed a methodology to optimise the transition pathway of a whole-energy system: EnergyScope Pathway. Like its original model, EnergyScope TD [19], this model represents a whole-energy system, is open-source, is documented, and optimises both the investments and hourly operations over a year. The code and documentation are available online (see [43] for the code and [44] for the documentation). On top of these, EnergyScope Pathway assesses the entire transition by linking representative years over the transition while keeping the linear programming approach and, consequently, a tractable formulation. Optimising the perfect foresight 2020-2050 transition takes less than 15 minutes on a personal laptop. This model accounts for society inertia to change, anticipated decommissioning of assets as well as their salvage values. The latter avoid penalising capital-intensive investments.

The present work also presents the application to the Belgian energy system. Being a densely populated country with a limited renewable potential and fossil-dominated primary mix (i.e. in 2020, 89.4% of it is based on non-renewable resources), Belgium represents a challenging case study towards carbon-neutrality. The main results highlight a budget of 1 004 b€ over the transition between 2020 and 2050. This represents roughly twice the actual Belgian annual GDP and is balanced between investment (i.e. assets-related) and operation (i.e. resources-related) costs. Investments are driven by the fleet of vehicles to be replaced (44%), while renewable deployment (20%), electrification of heat (6%), reinforcement of the grid (6%) or storage technologies (1%) are much lower. To achieve a cost-effective transition, all the options are used: more efficient technologies reduce by 34% the consumed primary energy between 2020 and 2050, the massive deployment intermittent energies (i.e. sun and wind) allows the production of 28% of the primary energy mix in 2050 and, eventually, import of expensive renewable energies: electricity from neighbours (9%) and renewable fuels (41%). To facilitate the integration of intermittent renewable, electrification and storage technologies are heavily used.

The model's consistency was assessed by comparing its results with those of similar studies, mainly utilising the TIMES-BE model, a non open-source model. While it can be challenging to conduct a detailed comparison due to limited accessibility and documentation of information in models, the key performance indicators such as primary energy, electrification, and annualised total system cost demonstrated consistent outcomes. An extensive comparison with the Plexos model [94] — a commercial model — showed that EnergyScope Pathway yielded similar results, but with significantly shorter computational time and modularity Waucquez [30]. Some differences were observed that were mainly due to the different selection of typical days (TDs) and difference in the salvage formulation of the objective formulation.

This paper additionally analysed an alternative approach to the perfect foresight: a myopic foresight. The latter optimises the design on rolling windows with a limited knowledge of the future. A comparison between both approaches showed small differences with the myopic approach while reducing the computational time by 55%. Moreover, the myopic approach allows a more realistic representation of the decision making process, such as revealing shocks over the transition. This approach will be used in future work to assess the techno-economical robustness of transition pathway.

Acknowledgment

This work was made possible thanks to the support of the Energy Transition Fund—FPS Economy and by the European Union's Horizon Europe program under Grant Agreement No 101075660.

A Tables of SETS, Variables and parameters.

The full list of new SETs, parameters and **Variables** are defined and summarised in Tables 4, 5 and 6, respectively.

Table 4: New SETs for pathway formulation.

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

[a]The set AGE gives for each technology ($tech$) at a phase (p) the phase when it has been built. However, the set PHASE does not cover all the cases. Indeed, if the technology has been built before YEAR_2020, another value is assigned to the set AGE. Either the technology has been built just the phase before YEAR_2020 ("*2015_2020*") or the technology has been built before ("*STILL_IN_USE*"). Section 2.2.1 illustrates the use of this parameter.

Table 5: New parameters for pathway formulation. Set indices as in Table 4

Parameter	**Units**	**Description**
$max_{inv,phase}(p)$	[€$_{2015}$]	Maximum investment per phase
t_{phase}	[y]	Phase period (default 5 years)[a]
$diff_{2015,phase}(p)$	[y]	Years difference between financial reference year (2015) and the phase[b].
$gwp_{limit,transition}$	[ktCO_2]	Maximum carbon dioxyde $(CO_2)_{eq}$ emissions during the transition.
$decom_{allowed}(p,p,tech)$	[-]	Allow a technology to be decommissioned[c]
$limit_{LT,renovation}$	[-]	Limit the change in low-temperature heat technologies during a phase[d]
$limit_{pass.mob,changes}$	[-]	Limit the change in passenger mobility technologies during a phase[d]
$limit_{freight,changes}$	[-]	Limit the change in freight mobility technologies during a phase[d]
$efficiency(y)$	[-]	Share of energy efficiency achievement compared to reference (2050).
$\tau_{phase}(p)$	[-]	Annualisation factor for investments during the phases.

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

[b]This parameter is only used to evaluate the annualisation factor, see Eq. (19).

[c]In a phase, when the decommissioning is not allowed ($decom_{allowed} = 0$), the variable ($\mathbf{F_{decom}}$) is forced to 0. See illustrations in Figure 4.

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

Table 6: New **Variables** for pathway formulation. All **Variables** are continuous and non-negative, unless otherwise indicated.

Variable	Units	Description
$\mathbf{F_{new}}$ (p'^{a},tech)	[GW]^{bc}	Installed capacity during a phase p' with respect to the main output
$\mathbf{F_{decom}}$(p,p'^{a},tech)	[GW]^{bc}	Decommissioned^{d} capacity built in phase p' during a phase p with respect to the main output
$\mathbf{F_{old}}$(p,tech)	[GW]^{bc}	Retired^{d} capacity during a phase p with respect to the main output
$\mathbf{C_{inv,phase}}(p)$	[M€/GW^{e}]	Phase total annualised investment cost
$\mathbf{C_{opex}}(y)$	[M€/GW^{e}]	Operational expenditure over a year
$\mathbf{C_{tot,opex}}$	[M€/GW^{e}]	Total operational expenditure over the transition
$\mathbf{C_{tot,capex}}$	[M€/GW^{e}]	Total capital expenditure over the transition
$\mathbf{C_{tot,trans}}$	[M€/GW^{e}]	Total transition cost
$\mathbf{GWP_{tot,trans}}$	[MtCO_2]	Total transition global warming potential
$\Delta_{\mathbf{change}}$ (p,$tech$)	[GW]^{bc}	Change in a technology used during a phase

[a] $p' \in PHASE \cup \{2015\_2020\}$.

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

[c][GWh] if $tech \in STO$

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

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

B Formulation choices

The proposed formulation is a result of several decisions that the developers have taken. These decisions reflect either the results of several tests, or a choice among different methods. This section shares the underlying reasons of these decisions. Moreover, as a key feature of the EnergyScope models is to have a short computational time, we will propose alternative formulations that will be tested and compared in Section 4.2.

B.1 Horizon initialisation

In reality, the first representative year (i.e. 2020) inherit from a mix of technologies that have different ages. However, in the proposed formulation (Eq. 11), we assume that all the technologies are built just before the first representative year. This approximation is wrong but avoid collecting the age of all the existing technologies. However, the impact of this approximation is limited. These capacities are fixed exogenously. Thus, they have almost no impact on the investment decisions and have a limited impact on the overall transition cost in view of the investments that will be made after.

B.2 Years linkage

Striking a balance between accuracy and complexity has been a challenge in creating a comprehensive and linear formulation to connect multiple years. Various formulations have been explored, and the currently proposed one emerged as the most favorable option. Opting for a simpler formulation to read, would imply the use of non-linear or integer formulation, which imply higher computational time. Or it would imply to compromise the accuracy of the model by, as an example, not specifying the deployment dates of technologies.

One might question the rationale behind the formulation presented in Section 2.2.1, which distinguishes between technologies decommissioned prematurely and those that have reached the end of their operational lifetime. This decision introduces two parameters, namely *age* and $decom_{allowed}$. There are two key reasons driving this choice. Firstly, the value of $\mathbf{F_{old}}$ is constrained by when the technology has been built (Eq. (10)). Consequently, combining the two types of technologies would over constrain Eq. (8). Secondly, the model permits the removal of a technology if it remains unused. This simplifies post-processing tasks, such as identifying when a technology becomes obsolete, and also aligns with realism by eliminating maintenance-related costs.

An additional motivation for the proposed formulation arises from the constraints of linear programming. In this context, it is not possible to create loops for setting values directly within the language. Therefore, any necessary preprocessing must be conducted in advance. Parameters are pre-defined and utilized to constrain variables, akin to a for-loop structure. This rationale justifies the introduction of the $decom_{allowed}$ parameter, which limits decommissioned capacity to its physically feasible range, as expressed in Eq. (9). Similarly, the AGE set is employed to impose constraints on the $\mathbf{F_{old}}$ variable, ensuring it remains within its physically feasible domain, as indicated in Eq. (10).

These choices resulted in four constraints (Eqs. (8)-(10)), one set and one parameter. This formulation has the following advantages: (i) cost and characteristics of technologies are year dependent; (ii) linear formulation; (iii) definition of feasible space during pre-processing; and (iv) distinction between decommissioned and end of life technologies. The disadvantages are: (i) pre-processing of parameters and set; and (ii) the efficiencies of technology depend on the year when they are used and not the year when they are built.

A way to mitigate the latter issue would be to add a dimension 'phase´ to the technologies ($\mathbf{F}$) and their operation ($\mathbf{F_t}$). As a consequence, several equations would have to be duplicated increasing the complexity with a negligible impact on the results.

B.3 Evolution of efficiency

Technological efficiencies are expected to undergo continuous improvement over time. These efficiency values are sourced from the Danish Energy Database (refer to [76], [77], and [78]). Between 2020 and 2050, the average efficiency is approximately 6%, though noteworthy advancements are observed in specific vehicle technologies, such as fuel cells.

The most pragmatic approach to incorporate these efficiency improvements is to maintain the technology's efficiency level at the time of its deployment. For instance, if a Combined Cycle Gas Turbine (CCGT) is constructed with an efficiency of 59% in 2020, its efficiency should remain consistent in 2025, rather than adopting the efficiency of a newly constructed CCGT in that year. This approach necessitates the inclusion of an additional dimension to all variables associated to efficiency, such as operation of technologies ($\mathbf{F_t}$), storage level and power.

To maintain a simple formulation, the authors chose to keep one efficiency per technology (i.e. the one of the representative year. Despite this approximation, it enhances model interoperability as it is the same formulation as in EnergyScope TD. In a prior study, a global sensitivity analysis (GSA) was conducted to evaluate the impact of efficiency [54]. The results revealed that the influence of efficiency on the objective function (total cost in the study) and decision-making was negligible. The only exception was observed in the private mobility sector, where there was a 6% variation in investment decisions between fuel cells and electric cars.

B.4 Cost and emissions of the transition

The impact of greenhouse gases GHG decreases with time as they transform into more stable forms, such as limestone for carbon dioxide CO_2. [95] highlights that the cycle period of GHG transformation is hard to estimate, but it is likely much longer than 500 years. To compare the impact of different GHG, the global warming potential (GWP)of these gases is expressed for a given time horizon, usually a century. As our time horizon is 30 years, we assume that their GWP is constant over the optimisation horizon.

The cost formulation proposed in Section 2.2.3 is inspired from Prina et al. [5] where it is broken down in investment, maintenance, operation and salvage value. In the proposed formulation, the salvage value accounts for the cost of technologies available after the time horizon. However, if a technology is removed prematurely, its salvage value is not accounted for. This approach is different from Prina et al. [5] where technology prematurely removed are, from our understanding, are imposed by the users and thus not mathematically optimised. We emphasize the importance of not accounting for the salvage value of a technology that is prematurely removed. If it wasn't the case, the model could install an expensive infrastructure only for five years and then remove it. Thus when removing a technology prematurely, the salvage value is not recovered at the end of the optimisation horizon.

In the proposed formulation, the numerical value of the cost is based on the one at the installation of the technology, not in 2050. Goffaux [96] analysed the impact of five different formulations, including and excluding technology decommissioning and using different annualisation factors. The results indicate that only one formulation has a major impact: accounting or not for decommissioned technologies. This conclusions is aligned with the work of Poncelet et al. [60], who emphasizes the importance of accounting for salvage value to prevent penalizing capital-intensive assets towards the end of the model horizon.

The study on the annualisation factor performed by [96], shows that there is a limited impact on the results. A variation in the storage capacity is observed with an increase of 10% capacity (GWh) when annualisation factor is lower. This trends reflect that a higher interest rates encourage later investments.

C Approaches to reduce the computational time: More detailed analysis

This appendix aims at digging more into the details of the differences observed between the computational time-saving approaches and the reference case (i.e. hourly perfect foresight model), presented in Section 4.2.

C.1 Myopic versus Perfect foresight

Similarly to Nerini, Keppo, and Strachan [61], Figure 14 shows that myopic optimisation ends up with a slightly more expensive energy transition by 2050 (i.e. +3.2 b€$_{2015}$), compared to the perfect foresight, despite the savings done at the early stages. Even though this over-cost is negligible compared to the overall cost of the transition (i.e. $\sim$1000 b€$_{2015}$), this is explained by the early investments in renewable technologies (i.e. PVs and wind turbines) boosted by the significant salvage value retrieved from investing in the consequent reinforcement of the grid.

Figure 15 highlights this as infrastructures and the electricity-technologies account respectively for 83.2 and 61.2 b€$_{2015}$ in 2030 whereas the overall cumulative investments, so far, are 421.3 b€$_{2015}$. The significant lifetime (e.g. 80 years) and investment cost (i.e. 368M€/GW$_{\text{VRES}}$ [44]) of the power grid, and, on a smaller scale, the district heating network, explain why the myopic optimisation opts for a higher investment in these infrastructures, at early stages. Similarly to what Keppo and Strubegger [97] observed in their studies, these early investments consequently lead to more investments, later in the transition, to renew technologies that have become too old before 2050: during the phase between 2045 and 2050, the myopic approach needs to invest in 9.2GW of PVs that have been installed 25 years before whereas the perfect

Table 7: Exhaustive general comparison between the three approaches: Perfect foresight with hourly resolution (PF), Myopic with hourly resolution (MY) and Perfect foresight with monthly resolution (MO). Differences with the reference case (PF) below 1% are not shown ($\simeq$) and ones above 10% are in bold.

		PF	**MY**	**MO**	Units
Computational time[a]		830	**373**	**2**	s
Costs in 2050	Total transition[b]	1004	$\simeq$	-2%	b€$_{2015}$
	Cumulative opex	528	$\simeq$	-3%	b€$_{2015}$
	Cumulative capex	636	$\simeq$	-2%	b€$_{2015}$
	Salvage value	160	-1%	-5%	b€$_{2015}$
Primary energy mix in 2050	Total	368.0	$\simeq$	+2%	TWh/y
	e-hydrogen	15.6	$\simeq$	+2%	TWh/y
	e-methane	41.0	+6%	**+51%**	TWh/y
	e-methanol	54.8	$\simeq$	$\simeq$	TWh/y
	e-ammonia	40.7	-10%	**+55%**	TWh/y
Electrification in 2050[c]	System[d]	63.3	$\simeq$	**-27%**	TWh$_e$
	Industrial heat[e]	12.3	-7%	**-98%**	TWh$_{th}$
	Decentralised heat[e]	73.9	$\simeq$	**-13%**	TWh$_{th}$
Year of full VRES-deployment	PV	2045	**2040**	**2040**	-
	Wind-offshore	2030	**2025**	**2025**	-
	Wind-onshore	2025	2025	2025	-

[a]These computational times were reached on a 2.4GHz 4-core machine.

[b]As detailed in Equation 16, the transition cost is the sum of the cumulative opex and capex, salvage value being deduced.

[c]The electrification of the other sectors (i.e. centralised heat (100%-heat pump), private (100%-BEV), public mobility (80%-train and tramway), freight mobility (25%-train) and non-energy demand (0%)) are identical between the three approaches and are, therefore, not presented in the table.

[d]The electrification of the system is computed as the difference between the total production of electricity and the end-use demand of electricity.

[e]The electrification of the industrial and decentralised heating sectors are expressed in terms of thermal energy (TWh$_{th}$) provided by electrified processes, respectively industrial resistors and decentralised electric heat pumps.

foresight, by smoothing its investments over the entire transition, has to renew only 2.5GW of PVs.

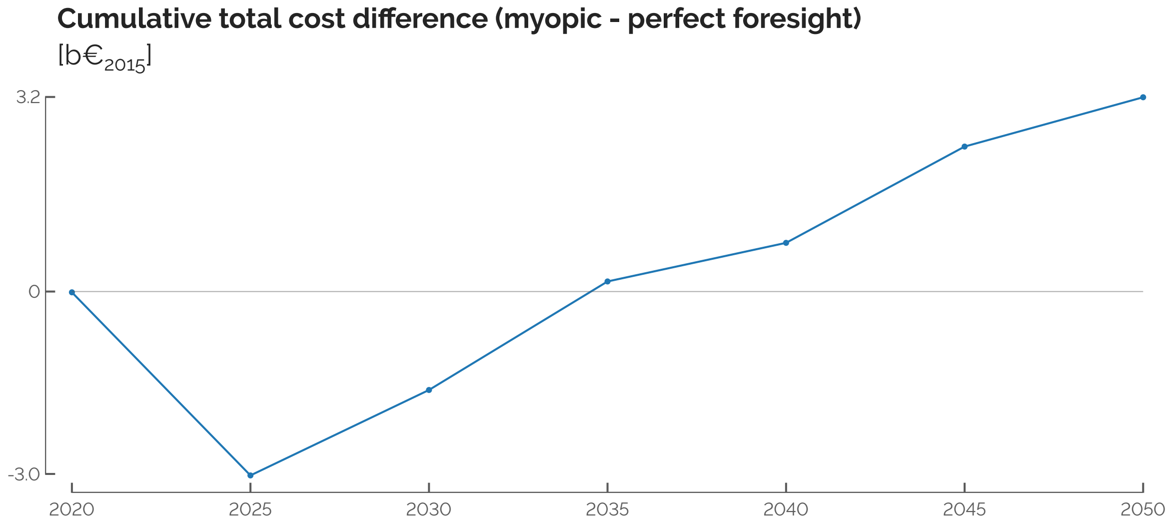

Figure 14: Cumulative total cost (i.e. opex+capex-salvage value) difference between the myopic and perfect foresight (PF) approaches. Positive values mean that the myopic approach is higher than perfect foresight.

In 2050, the capacities installed in the different sectors, the design of the system in other words, are very similar between the two approaches. The passenger and freight mobility sectors are the same where differences smaller than 1GW are observed in other sectors. More interestingly, the myopic optimisation tends to postpone the decommissioning of capacities when the loss of salvage values at the end of an optimisation window would be bigger than the maintenance cost. For instance, in the myopic approach, 0.8GW of industrial coal boilers will remain installed in 2045 and 2050 or 3.6GW of naphtha-crackers to produce HVC in 2040, whereas these technologies are not used. This is comparable to the "lock-ins" detailed in other studies [62, 97] where technologies installed at early stages of the transition remain in place.

Highlighted in Figure 16, the earlier availability of renewable (and intermittent) electricity consequently accelerates the electrification of the other sectors. For instance, in 2035, 3.7GW (+75%) more of industrial electric heaters to produce 5.1TWh/year (+130%) of additional industrial heat. In the low-temperature heat sector, decentralised and centralised electric heat pumps capacities are, respectively, 2.2GW (+19%) and 1GW (+8%) higher for each of the representative years between 2030 and 2045, to produce, around 7.8TWh/year (+23%) and 0.8TWh/year (+1%), at the expense of other technologies such as gas heat pumps. Finally, public trains substitute from 2035 a higher share of the CNG-buses.

In general, due to the formulation of the salvage value (see Equation 22), the myopic approach is more techno-oriented as investing more in technologies is beneficial, especially at the early stages of the transition. Therefore, before converging to a similar energy mix in 2050, the myopic system relies more on local renewables (e.g. solar and wind) than on importing renewable energy carriers (e.g. e-ammonia, e-methanol, e-hydrogen or e-methane), see Figure 16. In parallel, in the near term, the system relies on average more on conventional/non-renewable sources, like observed in other studies [97–99].

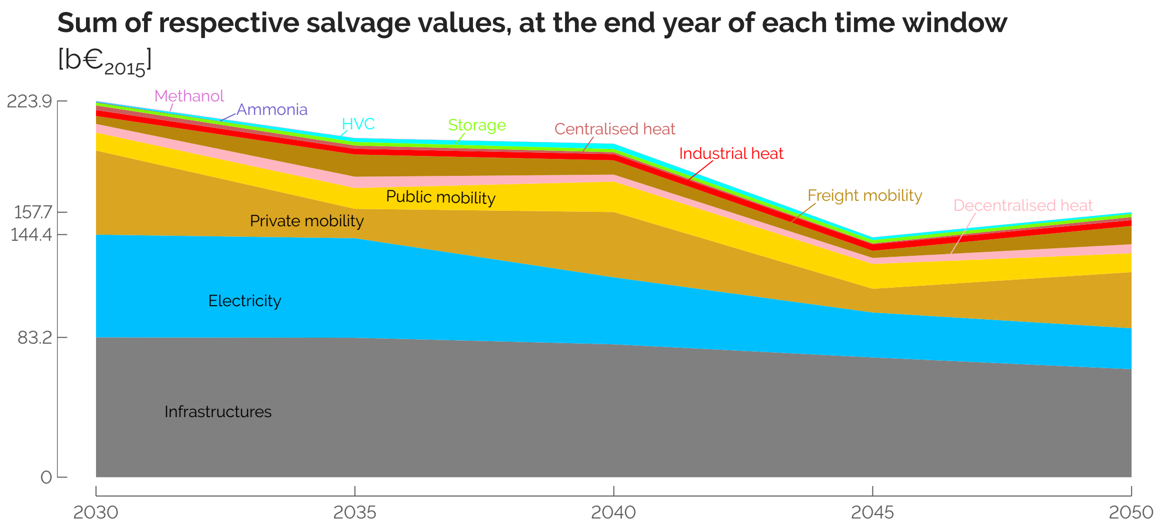

Figure 15: Sum of the respective salvage value of each sector, per end year of each time window. All together, these salvage values represent 223.9 b€$_{2015}$, 53% of the cumulative investment costs in 2030, and 157.7 b€$_{2015}$, 24% of the cumulative investment costs in 2050.

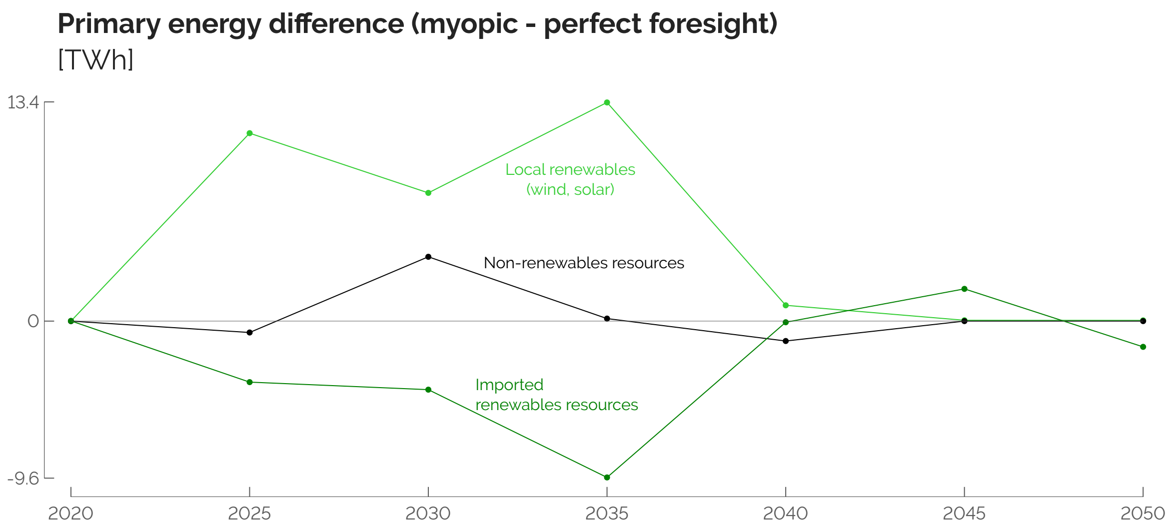

Figure 16: Primary energy resources difference between the myopic and perfect foresight (PF) approaches. Positive values mean that the myopic approach is higher than perfect foresight.

C.2 Monthly versus Hourly

This section compares the perfect foresight optimisation based on a monthly time resolution with the reference case (hourly time resolution). As displayed in Table 7, the main advantage of the monthly approach is its computational time (a reduction of 99.8% compared to the hourly resolution). This tractability represents a significant advantage when several thousands of runs are necessary, e.g. for uncertainty quantification as it has been performed in [48].

However, averaging time series of end-use demands and renewable productions brings some discrepancies. First and foremost, variable renewable energy sources (VRES) loose their intrinsic power intermittency [38]. This will have a series of consequences. Overall, this overestimates the uptake and emergence of solar and wind power generation and, consequently, overestimate their share in the primary electricity mix, especially at intermediate stages of the transition [38, 100] (see Figure 17). In line with these studies, the more there is VRES in the primary electricity mix, the higher is the error[9] with lower time resolution. In 2025 and 2050, where the share of VRES in the electricity primary mix is respectively 46% and 66%, this error goes from 10% to 18%.

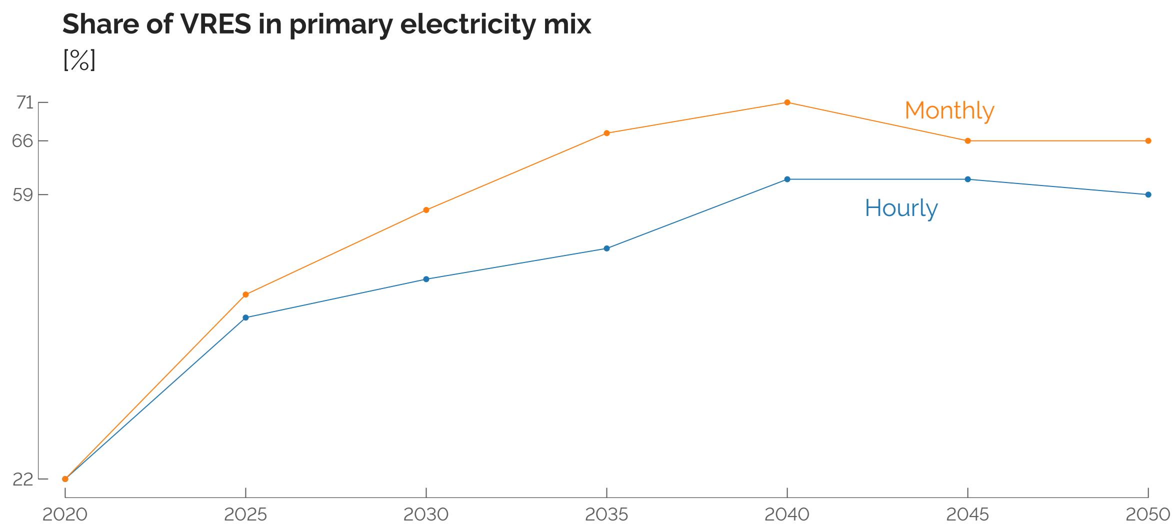

Figure 17: Share of VRES (i.e. solar and wind) in the electricity primary mix for the monthly and hourly time resolutions.

When considering the system overall, this averaged time-variability requires a more limited sector-coupling in the monthly model to absorb the intermittency of renewables. As listed in Table 7, industrial and decentralised heat demands are less electrified. This leads to 30% electrification of the overall system versus 36% for the hourly approach. This smaller production of electricity is done to the detriment of direct import of electricity, completely removed from the primary mix, as assumed to keep on having a higher global warming potential than conventional assets (e.g. CCGT running on gas and, later on, renewable gas and ammonia). Then, the generation mix in heating sectors or non-energy demands is less diversified, leading the sharper and later switch of resources and technologies. For instance, lignocellulosic biomass is "cannibalized" by industrial boilers to the detriment of biomass-to-methanol or HVC. Besides this, in general, we observe an overestimation of conventional technologies (e.g. running on gas or oil) generation, either by installing more capacities or having a higher load factor for similar

[9] Like Poncelet et al. [100], this error is defined as: $\sum_i \frac{|\text{supply share}_i^{MO} - \text{supply share}_i^{PF}|}{2}$, where index i runs over all technologies and import of electricity and the supply shares are expressed as a percentage.

capacities. In line with Poncelet et al. [100], this leads to an overall underestimation of the operational (and investment) costs, as detailed in Table 7.

Finally, in the mobility sectors, there is no difference between low and high time resolutions. This is due to the fact that these demands are assumed to stay the same over the different hours of the year (i.e. freight mobility) or have a favorite technology to supply them (e.g. BEV for private mobility).

C.3 Comparison without restriction on GHG

The outcomes of a model could be limited when the case study is too restrictive. Indeed, ones could argue that the comparison between myopic, monthly and perfect foresight are very similar as the energy system is strongly constrained in terms of GHG emissions.

In the following, we perform a similar comparison in the transition pathway without restricting the GHG emissions.

C.3.1 Reference case

Figure 18 illustrates the transition taken by Belgium without restriction on the GHG emissions.

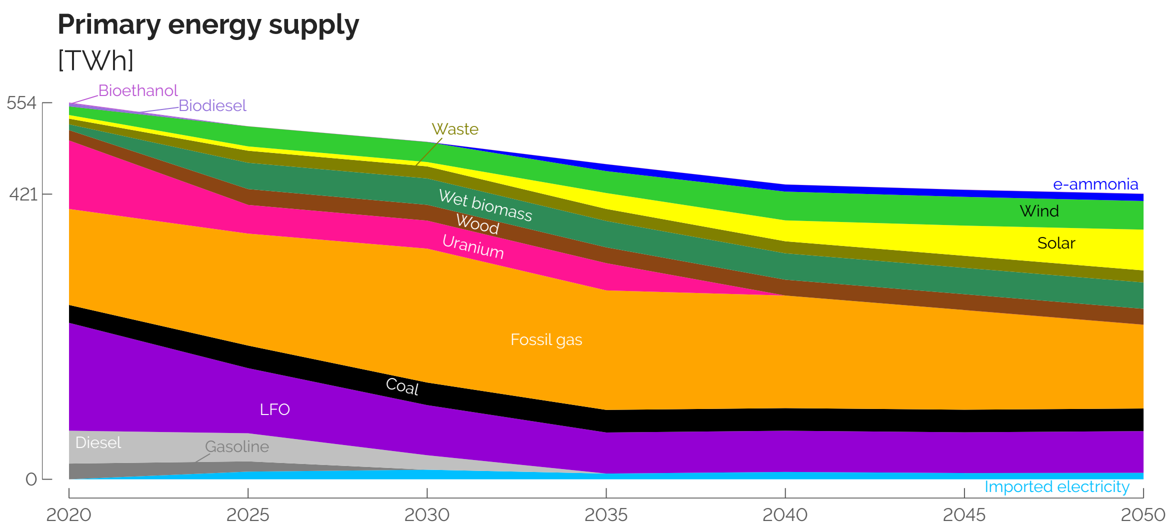

Figure 18: Primary energy mix of a non-constrained energy transition. In this results, carbon neutrality isn't reached in 2050. Some fossil fuels remain used.

Similar trends that for the defossilisation are observed: primary energy mix reduces, renewable energy integration rises and an electro-fuel is imported. However, some changes reflects the cheapest option that the system could utilise to reach a cheaper transition, such as using as little electro-fuels as possible. In this case, only e-ammonia is used for its end use demand.

Instead of analysing the energy system in details, the following parargaphs will investigate if the comparaison findings are consistent on a different case study.

C.3.2 Comparison with Myopic approach

Several key messages of the comparison have been summarised in Table 7. In the following paragraph we analyse how these conclusion are affected when the constraint on the GHG-emissions trajectory is removed.

First, considering the overall transition cost, the myopic approach keeps on making short-term savings, i.e. down to -0.2%, before ending up with a more expensive transition by 2050, i.e. +0.2%. Similarly to the case with an imposed GHG-emissions trajectory, myopic optimisation invests more, compared to the perfect foresight, at early stages into VRES technologies to benefit from the significant salvage values of the related grid infrastructures. In 2030, the salvage value of the infrastructures and electricity-generation technologies account for 80.2 and 56.2 b€$_{2015}$, respectively, whereas the overall CAPEX are 404.8 b€$_{2015}$ by then.

Then, in the case with a prescribed GHG-emissions trajectory, the myopic approach had to invest more by the end of the transition to renew PV installed more massively at early stages and that reached the end of their lifetime before the end of the transition. In the case without this emissions trajectory, there is less an urgency/need for integrating renewables in the system. Consequently, in the latter case, there is not such an extra-investment to make to renew too old renewable assets. On top of this, the slower uprise of VRES in the case without emissions trajectory leads to a smaller difference of electrification of the other sectors between the perfect foresight and myopic approaches.

Finally, even though the way to get there differs between the perfect foresight and the myopic approaches, the system designs by 2050 are very similar between these two in most of the sectors. The main observed difference is in the freight transport where diesel boats are preferred to gas boats. This can be looked as a result of the lock-in effect where choices made at early stages, due to the limited foresight, remain in place in the longer term.

In essence, when comparing perfect foresight and myopic approaches, distinctions arise in minor aspects, while the fundamental conclusions of Table 7 were verified. These variances have been elucidated in the preceding enumerated points and can primarily be attributed to the changes in the case study, rather than reflecting limitations inherent to the model or the comparative analysis itself.

C.3.3 Comparison with Monthly approach

Similarly to the previous section, this one compare the perfect foresight with the monthly approach. Findings summarised in Table 7 will be screened again in the following paragraphs.

The similarities are even stronger than in the previous section between the hourly and monthly models. The most important difference is the averaging over monthly values of the production of PV and wind turbines. This leads to an overestimation of the uptake and emergence of solar and wind power even though, in the case without the emissions trajectory, this uprise is slightly delayed since there is no more emissions constraint to respect (i.e. 2035 versus 2030 for the case with the emissions trajectory).

Then, in the case without the GWP-trajectory, we can draw the same conclusions as in Section C.2 when comparing the monthly and the hourly model. There is less sector-coupling (i.e. smaller electrification of the industrial and decentralised heating sectors) as less flexibility is needed to absorb the averaged intermittency of VRES. Import of electricity from abroad is also substituted by this cheaper and no more intermittent source of electricity provided by solar and wind. We also observe sort of a cannibalisation of the limited resources by specific sectors. For instance, industrial boilers uses the entire stock of woody biomass to the detriment of other processes like biomass-to-methanol or biomass-to-HVC. Finally, in the case without emissions-trajectory, there is also a drastic underestimation of the cumulative OPEX by 2050, i.e. -5.2%, as this “abundant” and free electricity provided by solar and wind reduces the need for other energy carriers like gas in CCGT, for instance.

In essence, when comparing hourly and monthly approaches, distinctions arise in negligible aspects, while the fundamental conclusions of Table 7 were verified.

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