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Evaluating the impact of storage technology construction's global warming potential and its uncertainties on EnergyScope projections for 2050

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Abstract

Integrating Life Cycle Assessment into long-term energy planning is essential to prevent decarbonisation strategies from inadvertently generating additional embodied emissions. This master thesis investigates how the Global Warming Potential of energy storage technologies, and the uncertainty associated with them, influence the optimal configuration of the Belgian energy system by 2050. The analysis relies on the EnergyScope Typical Days optimisation model, adapted to explicitly account for the Global warming potential of construction (GWP_{constr}) of storage technologies and the Global warming potential of operation (GWP_{op}) of imported renewable energy carriers.

The methodology combines deterministic optimisation, stochastic analysis using Polynomial Chaos Expansion, and tipping-point analysis to identify appearance/ disappearance thresholds and inter-technology transitions. Sensitivities are assessed through Sobol indices and correlation matrices. A complementary analysis also focuses on the GWP_{constr} of private mobility technologies, given the rapid and radical shifts observed in their optimised market shares.

Results show that integrating the GWP_{constr} for storage, combined with a change in the optimisation objective, significantly alters system trajectories: reallocations between storage types, changes in electrification rates, and shifts in trade-offs between local storage and renewable imports. Although the uncertainty on GWP_{constr} has a limited impact on global indicators, its sectoral effects are substantial: thermal storage, private mobility, and renewable imports respond strongly to variations, leading to notable technological substitutions. Introducing a realistic GWP_{op} for these imports, often assumed to be neutral, partly offsets the penalisation imposed on storage technologies, driving a strong resurgence of local storage and reducing reliance on carbon-intensive imported resources.

This work makes three key contributions: (i) the adaptation of EnergyScope TD to integrate the GWP_{constr} of storage and GWP_{op} of renewable imports; (ii) the original combination of optimisation, stochastic analysis, and tipping-point studies within a unified framework; (iii) highlighting the structural role of embodied emissions in prospective energy planning. The results emphasise the importance of systematically including these parameters and their uncertainty in long-term scenarios to design more resilient and low-carbon energy systems.

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Declaration of Generative AI and AI-assisted Technologies Usage

In the preparation of this thesis, I made occasional use of digital assistance tools. *ChatGPT* was used for improving the reformulation of certain passages, producing English translations and helping to optimize or clarify parts of the code. The *DeepL translator* was also used for additional translations. All analyses, methodological choices, interpretations and conclusions presented in this work are my own and I take full responsibility for their content.

Acronyms and notations

AMPL A Mathematical Programming Language.

BEV Battery Electric Vehicles.

CCGT Combined Cycle Gas Turbine.

CDF Cumulative Density Function.

Cent. centralised.

Dec. decentralised.

EPFL École Polytechnique Fédérale de Lausanne.

ESOM Energy System Optimization Model.

ET Emergence Threshold.

ETS Emissions Trading System.

EUD End-Use Demand.

EUT End-Use Type.

FCET Fuel Cell Electric Trucks.

FCEV Fuel Cell Electric Vehicles.

GHG GreenHouse Gases.

GSA Global Sensitivity Analysis.

GWP Global Warming Potential.

$\mathbf{GWP_{constr}}$ Global warming potential of construction.

GWP_{op} Global warming potential of operation.

HEV Hybrid Electric Vehicle.

HP Heat Pump.

HT High Temperature.

HVC High Value Chemical.

LCA Life Cycle Assessment.

LCI Life Cycle Inventory.

LCIA Life Cycle Impact Assessment.

LFO Light Fuel Oil.

LHV Lower Heating Value.

LOO Leave-One-Out.

LT Low Temperature.

MCS Monte Carlo Simulation.

NG Natural Gas.

NSGA-II Non-Dominated Sorting Genetic Algorithm 2.

PCE Polynomial Chaos Expansion.

PDF Probability Density Function.

PHEV Plug-in Hybrid Electric Vehicle.

PHS Pumped Hydro Storage.

POT Phase-Out Threshold.

PTES Pit Thermal Energy Storage.

PV Photovoltaic.

RE Renewable.

RHEIA Robust design optimization of renewable Hydrogen and dErIved energy cArrier systems.

RTP Reverse Tipping Point.

SHS Sensible Heat Storage.

Sto. storage.

TD Typical Days.

TP Tipping Point.

UQ Uncertainty quantification.

V2G Vehicle-To-Grid.

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Introduction

In 2023, nearly 75 % of Belgium's final energy consumption still came from fossil sources and more than 80 % of total energy supply was imported [23, 75]. At the same time, the European Union, through the Green Deal and the Fit for 55 package, requires a reduction of at least 55 % in greenhouse gas emissions by 2030 compared to 1990 levels, as well as carbon neutrality by 2050 [12, 13].
These figures highlight the scale of the challenge: to fundamentally transform an energy system still largely carbon-intensive, while ensuring a secure, affordable and resilient supply.

This transition will rely on the large-scale deployment of renewable energies, increased electrification of end uses and enhanced flexibility to manage intermittency [3, 61].
In this context, energy storage plays a strategic role: it enables smoothing of production, reduces dependence on imports and supports grid stability, especially in a highly renewable system [27, 30].

Yet, behind this key role lies a blind spot in energy optimization models. Tools such as Energyscope TD [25] are designed to determine optimal long-term technological pathways, but often rely on a partial assessment of emissions, ignoring or underestimating those related to infrastructure construction.
However, for certain storage technologies, the carbon footprint of this initial phase, measured through the Global Warming Potential (GWP), can represent a non-negligible share of the total impacts [28, 63].
Moreover, these values are subject to significant uncertainties, stemming from the lack of data, the variability of industrial processes and future technological developments [68].

This master thesis lies within this grey area of energy modelling.
It evaluates, using Energyscope TD, the impact of accounting for the Global Warning Potential of construction (GWP_{constr}) of storage technologies and the influence of their uncertainty on the robustness of optimized systems.
The analysis is extended to the Global Warning Potential of operation (GWP_{op}) of imported carriers, often considered as neutral, in order to correct potential biases in technological trade-offs.
Beyond the numerical results, the aim is to highlight transition dynamics, technological tipping points and structural interactions between storage, mobility and import flows.

The remainder of the master thesis is structured as follows: chapter 1 presents the state of the art and the theoretical framework, chapter 2 details the methodology and the modifications made to the Energyscope TD model, chapter 3 presents and discusses the results and finally, the conclusion summarises the contributions and outlines avenues for future research.

Chapter 1

Background

The energy transition towards carbon neutrality requires a detailed understanding of the environmental impacts associated with technological choices, as well as tools to guide these choices. This chapter provides an overview of approaches from the literature for assessing and optimising energy systems in a decarbonisation context. The first part introduces Life Cycle Assessment (LCA), the reference method for quantifying environmental impacts throughout the life cycle and examines its applications to energy pathways. The second part addresses the principles of energy modelling, its limitations when based on deterministic assumptions and the methods developed to integrate uncertainty into prospective analyses. Finally, the third part highlights the gaps identified in existing work, notably the limited consideration of the global warming potential related to the construction of storage technologies and the emissions associated with imported resources, paving the way for the research questions of this thesis.

1.1 Life Cycle Assessment (LCA)

LCA is an approach standardised by the ISO 14040 series, aiming to systematically assess the environmental impacts of a product, process, or service over its entire life cycle [28]. This method is structured around four main stages: definition of the goals and scope of the study, Life Cycle Inventory (LCI), Life Cycle Impact Assessment (LCIA) and interpretation of the results [77].

1.1.1 Methodology of LCA

Step 1 – Definition of the goals and scope of the study

This step involves specifying the purpose of the study, the selected functional unit, the system boundaries and the impact categories to be analysed. Temporal and

spatial boundaries play a key role in the interpretation of the results. Different approaches can be adopted [63]:

- **Cradle-to-grave**: covers all stages from raw material extraction to the end of life of the product.
- **Cradle-to-gate**: includes all stages up to the factory gate, excluding the use and end-of-life phases.
- **Cradle-to-cradle**: incorporates a circularity approach by considering closed-loop reuse or recycling.

In energy optimisation models such as EnergyScope TD, the cradle-to-gate approach is often preferred for assessing the impacts associated with the manufacturing of technologies. This choice is explained by the difficulty of reliably modelling the use and end-of-life phases in a prospective framework.

Step 2 – Life Cycle Inventory (LCI)

LCI consists of collecting and organising data related to the inflows and outflows of the studied system. This includes:

- the consumption of raw materials and energy,
- emissions to air, water and soil,
- waste generation.

These data can come from specialised databases such as *Ecoinvent*, which provide detailed and regularly updated environmental datasets [22]. They form the necessary input for the next stage of impact assessment.

Step 3 – Life Cycle Impact Assessment (LCIA)

LCIA consists of converting the inventoried flows into environmental indicators [63]. The impacts are grouped into categories such as climate change, acidification, resource depletion, or human toxicity.

The climate change category is the most widely used. It is assessed using the GWP, expressed in CO_2 equivalents. This indicator aggregates the effects of several GreenHouse Gases (GHG), such as methane or nitrous oxide, using characterisation factors. For example, 1 kg of CH_4 corresponds to approximately 25 kg CO_2eq [63].

Step 4 – Interpretation

Interpretation consists of critically analysing the results obtained in light of the initial objectives. It includes checking internal consistency, assessing associated uncertainties and, where appropriate, formulating recommendations. This stage also makes it possible to identify the parameters or processes that most influence environmental impacts and thus to prioritise improvement actions.

1.1.2 Application to energy systems

Applied to energy systems, LCA makes it possible to distinguish two main components of greenhouse gas emissions [81]:

- GWP_{constr}: includes emissions related to the manufacturing, transport and installation of technologies. It is particularly significant for short-lifetime systems, where frequent replacements generate recurring emissions. This component follows a cradle-to-gate approach, integrating all emissions up to the production site [36].
- GWP_{op}: corresponds to emissions generated during the use phase. It directly depends on the energy source used to operate the technology: the more decarbonised the energy, the lower this component. It may also include, where relevant, emissions from the transport of energy carriers.

In a carbon neutrality perspective, these two components can significantly influence technology choices and challenge the environmental competitiveness of certain options.

1.1.3 Sources of uncertainty in LCA

Like any modelling tool, LCA relies on a set of methodological choices and sometimes imprecise data, introducing various forms of uncertainty. These uncertainties are widely acknowledged in the literature, both in terms of data and model structure [4, 39, 73].

The first source of uncertainty concerns the quality of data used in LCI. Even primary data, such as temperature or humidity measurements, can be affected by errors, while secondary data, often derived from databases such as Ecoinvent [22], are usually based on approximations or averages that may not represent the real context [73]. This issue is particularly acute for emerging technologies, where data are even scarcer or more uncertain.

The next set of uncertainties stems from methodological choices: system boundaries, functional units, allocation rules, time horizons, or impact characterisation methods. While these decisions may seem technical, they directly affect the results [4]. For example, two studies using the same dataset but different methods can reach opposite conclusions.

Finally, in prospective LCA, a significant share of uncertainty comes from modelling future systems, whose technological structure, user behaviour and production conditions are still unknown [39]. This type of scenario-based uncertainty is difficult to reduce but can be addressed through stochastic approaches or sensitivity analyses.

As highlighted by Barahmand and Eikeland [4], these various forms of uncertainty may undermine result reliability if not explicitly addressed. Therefore, probabilistic or stochastic approaches are essential to test the robustness of outcomes.

1.2 Energy modelling and uncertainty management

The optimisation of long-term energy systems relies on modelling tools capable of representing the technological, economic and environmental complexity of the system under study. In the context of this work, this section first presents the role and characteristics of energy models used to guide transition pathways, as well as the inherent limitations of deterministic approaches. It then introduces methods for explicitly integrating uncertainty into these models, in particular stochastic approaches and global sensitivity analysis. Finally, it describes the methodological chain applied to EnergyScope TD to assess the impact of uncertainties on the global warming potential of certain technologies.

1.2.1 Role of models in energy planning

In the context of the energy transition, energy models are essential tools for guiding public policies and assessing possible decarbonisation pathways. They make it possible to identify the most suitable combinations of technologies to achieve climate objectives, such as carbon neutrality by 2050 [69].

Existing approaches differ in their level of detail and time horizon. Top-down models link the energy system to other macroeconomic sectors, but at the cost of a simplified representation of technologies, while bottom-up models describe energy pathways and equipment in detail, at the expense of fully integrating macroeconomic interactions [62]. Models can also be static, optimising a single reference year, or dynamic, simulating the transition over several decades. The

latter adopt either a perfect foresight approach, assuming complete knowledge of the future, or a myopic vision, which is more realistic but potentially suboptimal at the start of the period [62].

To be relevant in a prospective context, these models must integrate the temporal variability of renewables, cover all final energy uses (electricity, heat, mobility), jointly optimise investments and operations and remain sufficiently fast in computation to allow the exploration of multiple scenarios [69].

Among widely used energy planning models [52], OSeMOSYS is a modular, open-source linear optimisation model suitable for national long-term scenarios [41, 57]. TIMES, developed within the ETSAP framework, offers a high level of technological and economic detail but often requires licences and provides more limited transparency [41].

In this context, EnergyScope TD stands out for its multisectoral bottom-up nature, temporal granularity, open-source formulation and computational speed [52]. Developed by UCLouvain and EPFL, it covers all final uses and simultaneously optimises investments and operations. Validated for the Belgian context in the doctoral thesis of Limpens [52], it offers a relevant compromise between temporal precision, sectoral coverage and computation time, while allowing direct integration of environmental indicators such as GWP_{constr} and GWP_{op}.

However, like most techno-economic models, EnergyScope TD relies on deterministic assumptions for a large number of parameters, whether related to costs, performance, or emission factors. This simplification, while necessary to ensure computational feasibility, may influence the relevance of the optimal pathways obtained. The limitations associated with this approach and the ways in which they can be addressed are presented in the following subsection.

1.2.2 Limitations of deterministic models

Deterministic energy models rely on a set of assumptions fixed a priori regarding key parameters such as investment costs, technological efficiencies, emission factors, or resource availability. While these assumptions are essential to establish a modelling framework, their rigidity can introduce significant biases and lead to inappropriate recommendations.

Several studies show that most energy system optimisation analyses do not explicitly account for uncertainty [87]. However, this omission can lead to inadequate recommendations when initial conditions change. For example, historically low

natural gas prices have favoured overinvestment in Combined Cycle Gas Turbine (CCGT) plants in Europe, illustrating how a supposedly stable context can quickly render optimal decisions obsolete [68]. More generally, a static description of technologies may overlook possible evolutions in their performance, environmental impacts, or costs, leading to biased results. This strong dependence on initial assumptions raises questions about the robustness of the resulting optimal pathways.

The parameters used in energy models cover a wide range of technical, economic, environmental and socio-political dimensions. The vast majority of these are subject to different types of uncertainties [19]:

- **Epistemic uncertainties**: related to a lack of knowledge or incomplete data, they can be at least partially reduced through measurement campaigns, improved databases, or better characterisation of technologies.
- **Aleatory uncertainties**: resulting from phenomena that are intrinsically unpredictable over time, they are considered irreducible and must be incorporated into the assessment of solution robustness.

If these uncertainties are not taken into account, the model implicitly assumes that future trajectories are perfectly known, which is unrealistic in a rapidly changing energy context. To address this, a growing number of studies use probabilistic or stochastic approaches to explore a wider range of possible conditions. These methods make it possible to assess the sensitivity of results to parameter variations, identify those that most influence the optimal configuration of the system and thus propose solutions that are more robust to structural uncertainties about the future.

In this work, due to insufficient data to accurately characterise probability distributions, the assumption retained, in line with Rixhon [68], is that uncertain parameters follow a uniform distribution, which leads to a stochastic-type implementation.

1.2.3 Uncertainty management approaches

According to Rixhon et al. [69], Uncertainty quantification (UQ) is one of the major challenges in prospective modelling of bottom-up energy models. Neglecting this dimension can lead to underestimating the actual costs of a complete carbon-neutral energy system, particularly in long-term scenarios where assumptions are highly subject to variability. Aware of this limitation, numerous studies have proposed methods to explicitly integrate uncertainty into Energy System Optimization Model (ESOM) [62, 68]. These approaches aim to assess the impact of uncertain parameters on modelling results and are particularly relevant for tools such as

EnergyScope TD, where parameters derived from LCA can influence the optimal composition of the energy mix.

Stochastic analysis and sensitivity analysis

Stochastic analysis consists in representing certain input parameters as random variables following a given probability distribution. By sampling from these distributions and repeatedly running the model, one obtains a distribution of results that characterises the variability and robustness of the optimal pathways [19]. This approach relies on two key elements: the definition of uncertainty distributions and the generation of input sets through an appropriate experimental design.

Sensitivity analysis quantifies the relative influence of each uncertain parameter on the results [84]. It can be local (isolated variation of a parameter around a reference point) or global, with the latter being most appropriate for multi-parameter systems such as ESOM. Global Sensitivity Analysis (GSA) often uses the data produced by stochastic analysis to compute indicators such as Sobol indices [19], which decompose the total variance into main effects and interaction effects between parameters.

Sampling methods and Sobol sequences

The choice of sampling method directly influences the convergence and quality of the exploration of the uncertainty space. Quasi-random Sobol sequences ensure uniform coverage of the multidimensional space, limiting poorly explored areas or excessive concentrations of points [85]. They are commonly used for the computation of Sobol indices as they offer a good compromise between exhaustiveness and computational cost.

1.2.4 Uncertainty quantification methods: Polynomial Chaos Expansion and Sobol indices

Monte Carlo and variants

Monte Carlo Simulation (MCS) is the reference method for propagating uncertainty and estimating the statistical moments of outputs [35]. Although it is simple and robust, it requires a large number of model evaluations, which can be prohibitive for complex tools. Variants such as Latin Hypercube Sampling or Sobol sequences can improve efficiency. An alternative is to build a metamodel, for example using Kriging, support vector machines, or PCE, allowing the model response to be approximated at lower cost [19].

Polynomial Chaos Expansion (PCE)

PCE is an efficient method for uncertainty quantification and global sensitivity analysis [68]. It approximates the output $Y(\xi)$ of a model by combining orthogonal polynomials $\Psi_\alpha(\xi)$ of the uncertain variables ξ:

$$\hat{Y}(\xi) = \sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha(\xi) \tag{1.1}$$

where y_α are the coefficients to be estimated and $\mathcal{A}$ is the set of multi-indices according to a truncation scheme. Once the metamodel is built from an initial sample, the statistical moments (mean, variance) and Sobol indices can be obtained analytically, avoiding additional costly simulations.

Sobol indices

Sobol indices measure the proportion of output variance attributable to a parameter, alone or in interaction [85, 68]. The total index of a parameter i is defined as:

$$S_i^T = \frac{\sum_{\alpha \in \mathcal{A}_i^T} y_\alpha^2}{\sum_{i \neq 0} y_\alpha^2} \quad \mathcal{A}_i^T = \{\alpha \in A \mid \alpha_i > 0\} \tag{1.2}$$

A parameter is generally considered negligible if $S_i^T < 1/d$, with d the number of uncertain parameters [68]. Sobol indices thus make it possible to rank the sources of uncertainty and guide reduction efforts.

1.3 Research context, gaps and problem statement

In the scientific literature as well as in energy optimisation models, several components of LCA remain neglected or simplified. This is particularly true for the $\mathrm{GWP}_{\mathrm{constr}}$ of many technologies, including energy storage systems [52], but also for mobility, freight and certain conversion infrastructures [43, 51]. For the sake of simplification, $\mathrm{GWP}_{\mathrm{op}}$ is generally accounted for fossil resources, but often ignored for renewable resources, whether local or imported [43]. In EnergyScope TD, for example, imported electrofuels are considered "climate neutral" [68], which excludes transport-related emissions, although these are estimated at between 5 % and 10 % of the full life cycle [68].

Such assumptions can bias results by overestimating the benefits of certain options while underestimating others. Their impact is particularly critical in a deep decarbonisation context: as operational emissions decrease, those associated with infrastructure construction account for an increasing share of residual emissions,

potentially becoming dominant in the long term [70]. The global warming potential associated with construction thus becomes a strategic lever, still too rarely integrated, for achieving carbon neutrality.

This work is part of a prospective assessment applied to Belgium by 2050, using the EnergyScope TD model enhanced with environmental and economic constraints. The objective is to explicitly integrate the GWP_{constr} of storage technologies and assess how their uncertainty, linked to the variability of future technologies, the limitations of LCA databases or the methodological assumptions adopted, affects the optimal composition of the energy system and the robustness of the projected trajectories. Special attention is given to cross-effects with assumptions on the GWP_{op} of imported resources, as well as to interactions between storage, mobility and imports. The assessment of these uncertainties is based on a stochastic approach, combining sampling of uncertain parameters and global sensitivity analysis to quantify their relative influence on the model results.

In this context, this master thesis aims to answer the following questions:

1. What is the impact of accounting for the GWP_{constr} of storage technologies on the optimization results of the EnergyScope TD model by 2050?
2. To what extent does uncertainty in the construction-related GWP of storage technologies affect the robustness of the optimized energy system?
3. What are the critical GWP thresholds beyond which a storage or mobility technology disappears from the energy mix or, conversely, becomes dominant?
4. How do assumptions about the GWP_{op} of imported energy vectors alter the balance between local storage, electrification and dependence on imports?
5. What structural links can be identified between storage technologies, mobility trajectories and import flows in optimized energy systems?

Chapter 2

Case study and methodology

This chapter presents the methodological framework and the case study on which this master thesis is based. The analysis focuses on Belgium's energy transition by 2050, using the EnergyScope TD optimisation model as the central tool, complemented by uncertainty analyses and technological threshold assessments. The diagram in Figure 2.1 illustrates the overall sequence, from input data to the integration of uncertainty quantification methods and tipping point identification.

The developed methodology adopts a dual perspective: economic, through the evaluation of the system's total costs and environmental, through the analysis of greenhouse gas emissions over the full life cycle of technologies. It specifically integrates the GWP_{constr} of energy storage systems, as well as the GWP_{op} of imported energy carriers. This dual approach makes it possible to explore trade-offs between economic performance and climate impact and to assess the robustness of technological pathways under different assumptions.

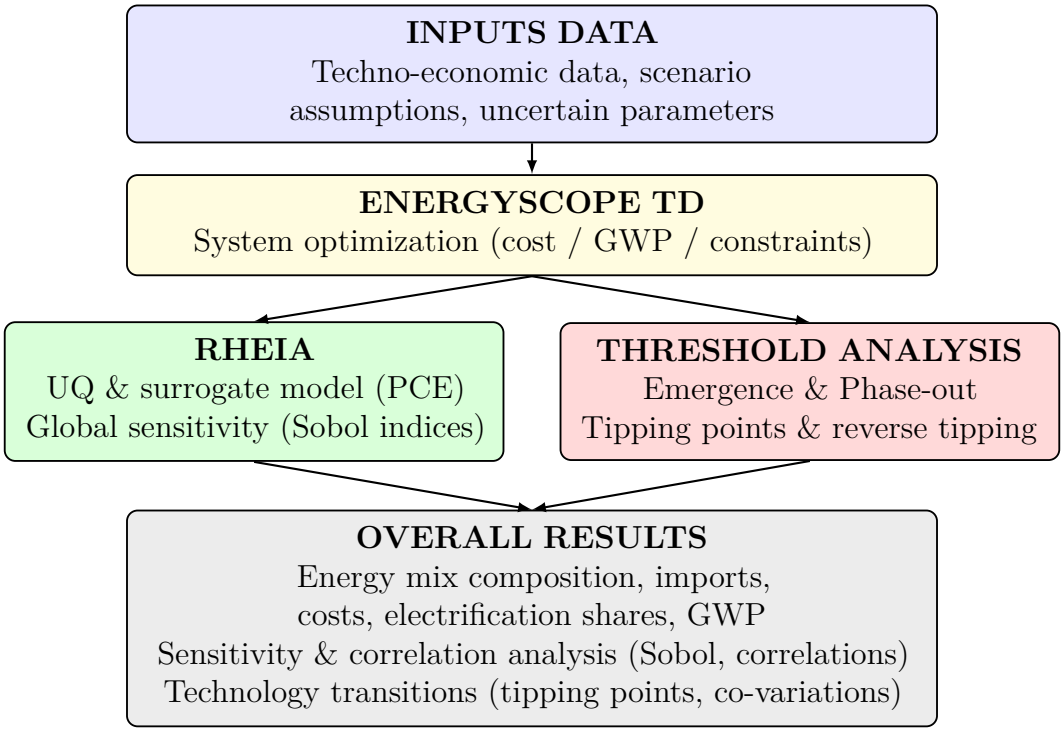


Figure 2.1: Overview from inputs to Energyscope TD, branching to RHEIA and threshold analysis, converging to global results.

The remainder of this chapter first presents the Belgian energy context by 2050, then describes EnergyScope TD and the modifications made to it. The methodological approaches implemented for threshold analysis, co-variation study and uncertainty quantification are then detailed, ensuring a logical transition to the chapter dedicated to results.

2.1 Belgian energy context by 2050

This section describes the main structural, technical and policy characteristics of the Belgian energy system as anticipated by 2050. It forms the contextual foundation for the modelling work carried out in this thesis.

By presenting the national objectives, the expected transformations of the energy mix and the associated economic and environmental constraints, this overview highlights the specific challenges and opportunities of Belgium's energy transition.

2.1.1 National objectives and structural projections

By 2050, Belgium will need to undergo a deep transformation of its energy system to meet its climate goals. This transition relies on four major pillars: reducing energy demand, electrifying end-uses, massively developing renewable energies and ensuring system flexibility.

Structural transformation of the energy mix

Total energy demand in the country, currently around 400 TW h[71], is expected to decrease by 25 % to 45 % by 2050, thanks to a combination of electrification and improvements in energy efficiency [33]. At the same time, electricity consumption could double or even triple, reaching between 155 TW h and 170 TW h of final demand [59, 33]. This increase is mainly due to growing electrification in road transport, residential heating and some industrial sectors [59, 11].

The development of electric vehicles, heat pumps and building retrofitting are among the key levers [59]. However, some sectors, such as heavy industry or maritime transport, remain difficult to electrify. Low-carbon carriers such as hydrogen, synthetic methane, or ammonia could therefore represent between 12 % and 38 % of final energy demand [33].

To meet the growing electricity demand, Belgium plans to massively expand its renewable capacity, mainly through solar Photovoltaic (PV) and onshore/offshore wind. The target is to reach between 65 GW and 80 GW of installed capacity by 2050 [59], requiring significant investments, particularly in North Sea offshore wind projects such as the North Sea Wind Power Hub [55].

In parallel with the rise of renewables, nuclear energy remains a structural uncertainty. The initially planned phase-out in 2025 has been postponed, with two reactors extended until 2035 [1] and discussions are underway about building new reactors in the longer term [24].

Structure of mobility demand

Mobility is a strategic lever for the transition. Private cars account for nearly 48 % of passenger mobility, a usage difficult to shift towards public transport. In freight, rail and inland waterways handle up to 25 % and 30 % of demand respectively, while the rest is dominated by road transport [69]. These distributions directly influence the need for alternative energy carriers.

2.1.2 Flexibility needs: storage and imports

Integrating variable renewable sources disrupts the traditional balance of a dispatchable system. Flexibility thus becomes a sine qua non condition for stability, in both the short and long term [59, 11].

In the short term, daily flexibility is provided by stationary batteries and Vehicle-To-Grid (V2G), which smooth out daily variations linked to day/night cycles [59]. This mechanism uses electric vehicle batteries as decentralised storage units that can feed electricity back into the grid during consumption peaks, or store surplus renewable electricity during production lows [27].

In the medium term, structural flexibility relies on growing interconnection with neighbouring countries, enabling imports of up to 32 TW h of electricity per year by 2050 [59]. This figure aligns with the 30 % limit of final electricity demand proposed by Rixhon et al. [69] as a reasonable dependency threshold. In this thesis, the variability of import dependency is integrated into EnergyScope TD simulations to assess its impact on the structure of the energy system.

In the long term, seasonal flexibility requires energy carriers such as hydrogen or e-methane, capable of storing renewable surpluses over extended periods [11]. Their modelling in EnergyScope TD allows assessment of their complementarity with batteries and imports, especially under stringent climate constraints.

Additional flexibility challenges

Given its limited potential, Belgium will have to import a substantial share of clean molecules [59, 69]. This strategy is especially relevant for hard-to-electrify uses, such as aviation or maritime shipping. However, their role remains marginal in cost-minimisation scenarios, where direct electrification dominates.

Sobriety policies such as car sharing, increased public transport use, or reduction of built surfaces, help lower global demand and thus reduce flexibility and infrastructure needs. Their indirect role in stabilising the energy system is crucial, as evidenced by the differences in annual investment between low-demand and high-demand scenarios [6].

These transformations converge towards a decentralised, supply-driven energy system, in contrast to the historical demand-driven model. This shift requires not only adapted technologies, but also institutional tools, flexibility markets, forecasting capacities and integrated governance at the European level [59, 11].

2.1.3 Economic and environmental constraints

The shift to carbon neutrality implies massive investments while complying with strong climate constraints.

Transition costs and investments

In 2015, the Belgian energy system emitted 127 Mt CO_2eq/y at a cost of 43.6 G€/y [69]. With optimal technologies, a carbon-neutral system could cost around 59.1 G€/y, considering only operational emissions.

The macroeconomic analysis by Bekaert et al. [5] estimates additional investments of 415 G€ by 2050. More than half of this amount is dedicated to building retrofits. The scale of these costs justifies the use of techno-economic models like EnergyScope TD to identify robust and economically viable pathways.

Depending on the assumptions, investment levels vary significantly. Promoting alternatives to individual car use, for example, could reduce overall system costs by 6 % [6].

Climate and regulatory constraints

According to Climate Change, residual greenhouse gas emissions could be reduced to between 10.2 Mt CO_2eq/y and 12 Mt CO_2eq/y by 2050, although this estimate does not cover all sources and sinks. The analysis is based on the Emissions Trading System (ETS) principle, which limits emissions through a quota trading system. This mechanism allocates emission rights to companies, which can trade them on a carbon market. Emitters exceeding their quotas must purchase additional rights, while low emitters can sell their surplus [10]. This mechanism is sometimes criticised for its limited long-term effectiveness, particularly in cases of overallocation or low carbon prices.

Rather than imposing a precise emissions reduction trajectory, some studies propose using a carbon budget, ie the total allowable emissions over a given period. This is the case in the study by Rixhon et al. [69], which sets a cap of 1.2 Gt CO_2eq for the 2020–2050 period. This budget constrains the entire energy trajectory without explicitly requiring zero emissions by 2050. It represents only ten years of emissions at the current rate, underlining the urgency of rapid structural transformation.

2.1.4 Specificities of the Belgian system

Belgium is a relevant case study for testing optimised energy transition strategies for several reasons.

First, its high urban and industrial density, combined with a historical reliance on fossil fuels and nuclear, makes decarbonisation particularly complex [5, 68].

Second, the domestic renewable potential is limited, especially for ground-mounted solar and onshore wind, increasing reliance on imports or storage [52].

Lastly, despite its small size, Belgium has a robust and highly interconnected energy network with its neighbours, enabling advanced mechanisms for flexibility and cross-border exchange [52].

These features make Belgium a suitable environment for testing optimisation models like EnergyScope TD, particularly under a GWP-oriented approach. They also allow observation of the effects of extreme constraints on complex systems, as explored in this thesis.

2.2 Energy system modeling with EnergyScope TD

This section describes the functioning of the EnergyScope TD model, which constitutes the core of the modeling used in this study. The objective is to present its operating logic, the types of data involved, the optimization process, as well as the model's strengths and limitations.

The general architecture of the EnergyScope TD model is shown in Figure 2.2 providing an overview of its main components before detailing each element in the following subsections.

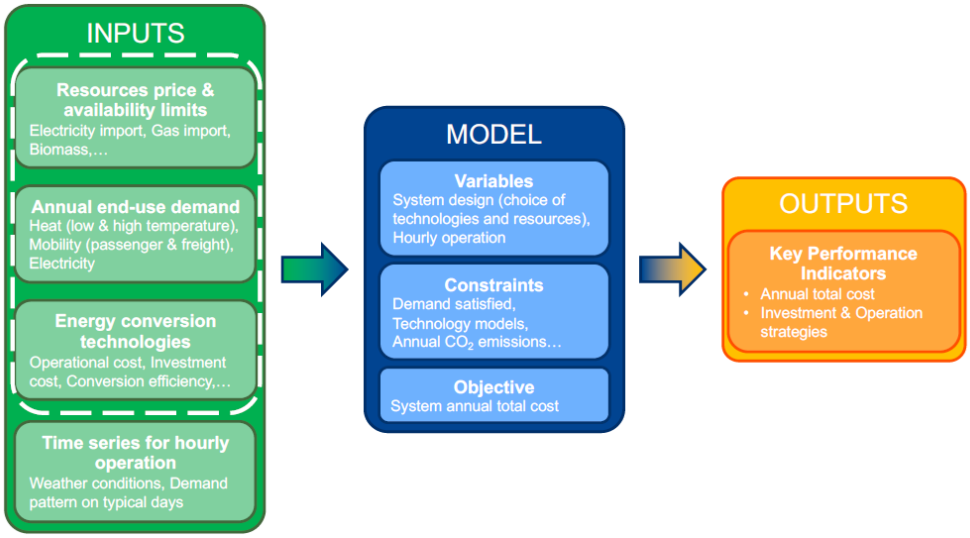


Figure 2.2: General structure of the EnergyScope TD model, showing the input data, the model formulation and the key performance indicators obtained as outputs. Taken from [69].

2.2.1 Model description

EnergyScope Typical Days is an energy optimization tool developed to model and plan long-term energy systems. It is based on a linear programming approach that determines the optimal technological mix to meet a country's energy demand, while minimizing either total costs or greenhouse gas emissions, subject to a set of technical, economic and environmental constraints.

The fundamental principle of the model is energy balance: at every time step represented in the simulation, the energy produced or imported must exactly match the energy demanded. To achieve this, EnergyScope TD adjusts two key types of variables: on the one hand, the installed capacities of different technologies (production, conversion and storage) and on the other hand, the hourly energy flows, i.e., the actual operation of these technologies over time. A third important variable is the storage level, which enables the system to smooth out temporal imbalances between supply and demand.

To realistically represent hourly variability while maintaining a reasonable computational load, the model adopts a typical-day approach. Twelve representative days are selected and applied to portions of the year that share similar characteristics.

The implementation of EnergyScope TD follows a multi-step structure. The first

step consists in defining the energy system to be modeled. This includes the characterization of final energy demand (residential heating, transport, industrial use, etc.), the identification of available resources (renewables, fossil fuels, nuclear, imports) and the selection of deployable energy technologies (power plants, heat pumps, electrolyzers, batteries, etc.).

In a second step, the data are preprocessed and stored in the form of DataFrames. These data are then converted into the AMPL format used for optimization.

The actual optimization is performed using the AMPL solver. At the end of this process, EnergyScope TD provides an optimized solution that includes, among other things, the installed capacities, the energy flows per technology, the total system cost and the associated CO_2 emissions.

The total system cost is defined as the sum of annualized investment costs, annual maintenance costs and the cost of purchasing energy resources.

$$C_{\text{tot}} = \sum_{i \in \text{Technologies}} \left(C_{\text{inv},i} + C_{\text{maint},i} \right) + \sum_{j \in \text{Resources}} C_{\text{res},j} \tag{2.1}$$

The optimization is therefore performed by adjusting technological investments and resource use in order to minimize this total cost, while complying with constraints such as: CO_2 emission limits, maximum technology capacities, minimum efficiency thresholds, resource availability and hourly energy balance requirements [51].

Our reference scenario is based on cost minimization while imposing a strict constraint on annual CO_2 emissions. This means that the selected technologies are economically optimal, but not necessarily the most efficient from a climate or environmental perspective. This is why it is useful to explore alternative optimization objectives, such as emission minimization, in order to assess possible trade-offs between sustainability and cost-effectiveness.

2.2.2 Inputs of Energyscope TD

The EnergyScope TD model relies on three main categories of input data [43] to simulate and optimize the energy system: available resources, deployable technologies and the energy demand to be met.

Energy resources

The energy resources integrated into the model are divided into two groups: endogenous resources, produced locally in Belgium and exogenous resources, imported from abroad.

Endogenous resources include renewable sources such as solar energy, wind, hydroelectricity, biomass and waste. Except for waste, all are considered carbon neutral. However, their exploitation is constrained by geographical, technical and social acceptance factors, which are represented in the model through a limit on installable capacity and an hourly production profile based on capacity factors.

Exogenous resources include imported electricity, biofuels, synthetic fuels and fossil fuels. Their availability is limited in the model to reflect geopolitical constraints or energy sovereignty objectives.

Energy technologies

The technologies considered in EnergyScope cover both conversion systems (for electricity, heat, fuels...) and energy storage technologies. Each is described by a set of technical and economic parameters: investment cost, maintenance cost, lifetime, energy efficiency and greenhouse gas emissions.

A dedicated input file gathers the input and output flows of each technology in tabular form. These flows are used to model the entire energy chain, from primary resources to final energy services.

The model also integrates GWP emissions associated with each technology, for both construction and operational phases, expressed in kg CO_2eq per unit of useful energy produced.

Energy demand

Instead of relying on final energy consumption, EnergyScope adopts an End-Use Demand (EUD) oriented approach. This methodology allows for a more accurate representation of real energy service needs (heating, mobility, lighting, etc.), independently of the energy vector used.

Demand is subdivided into four main sectors: residential, tertiary, industrial and transport, with further breakdowns according to End-Use Type (EUT). For example, the mobility sector distinguishes passenger transport, expressed in passenger-kilometers, from freight transport, expressed in ton-kilometers. The

thermal sector distinguishes between low-temperature heat, used for domestic heating or hot water and high-temperature heat used in industrial processes.

As for electricity, the model distinguishes a constant share over time, the base load and a variable share based on an hourly input time series. To avoid double counting, electricity used for heating and mobility is excluded from gross electricity demand.

Finally, the model also accounts for non-energy uses such as demand for ammonia, methanol, or High Value Chemical (HVC), which are essential for the industrial sector.

2.2.3 Outputs of Energyscope TD

The outputs correspond to the results of the optimization process and describe the optimal configuration of the energy system for the studied scenario. They include the installed capacity of each technology, as well as their hourly production profile modeled using typical days. The model also provides economic indicators, such as total costs and their breakdown into investment, operation and maintenance, as well as environmental indicators, notably greenhouse gas emissions associated with the construction of technologies and the use of resources. Finally, the energy flows between vectors and sectors are detailed, enabling the analysis of intersectoral interactions and the structural dependencies of the system [25].

2.2.4 Strengths of EnergyScope TD

EnergyScope TD stands out for a set of features that make it a powerful tool for prospective energy system analysis. Its detailed representation of intersectoral interactions, temporal variations and complex techno-economic constraints [25] directly stems from its bottom-up approach, which enables a fine modelling of the sectors and technologies described in the state of the art.

Unlike other, more opaque models, EnergyScope TD is fully open-source [51], meeting the transparency requirement mentioned earlier: all assumptions, data and calculations are accessible, verifiable and modifiable, which facilitates adaptation to different contexts and prospective scenarios.

Computational efficiency is ensured through the use of typical days, an essential method for representing the temporal variability of renewables while avoiding the burden of a full hourly resolution [51]. This approach captures daily and seasonal dynamics while keeping computational costs reasonable, thus allowing the

exploration of a wide range of scenarios.

Finally, its modular structure offers high scalability: each component can be modified or replaced without revalidating the entire model [25]. This modularity, in line with the flexibility needs identified in the literature, facilitates the integration of new technologies or constraints, including those specific to this work like GWP_{constr} or GWP_{op} of imports.

2.2.5 Limitations of EnergyScope

Despite its many advantages, the EnergyScope TD model presents several limitations that should be taken into account when interpreting the results.

First, its spatial resolution is limited to a single geographical cell, representing one regional area connected to neighboring countries through simplified assumptions. The model does not allow for detailed simulation of energy exchanges between multiple regions or countries, such as cross-border interactions or electricity trade, which are nonetheless essential for a global analysis of energy systems [51].

Second, the techno-economic resolution remains simplified. From a technical point of view, most technologies can ramp up from zero to full capacity within one hour, except for nuclear, which does not always reflect physical realities. From an economic standpoint, operating costs are mainly represented by resource purchases, while maintenance costs are assumed to be proportional to installed capacity [51].

The model is also constrained by a time horizon limited to a single year. It is a snapshot model that does not take into account the current state of the energy system nor its dynamic evolution over time [51].

Mathematically, EnergyScope TD is formulated as a continuous deterministic linear optimization problem. All input data are assumed to be known in advance and the model converges to a single optimum. This framework can produce results that are sensitive to parameter variations, which limits its robustness in the face of uncertainty and can be particularly problematic when projecting to 2050. To address this limitation, uncertainty analysis techniques may be used, provided the computation time is low enough to allow for adequate sampling [51].

Furthermore, the model relies on a fixed energy demand expressed in terms of End-Use Demand, without a dynamic representation of demand-side flexibility. Mechanisms such as demand response, load shifting, or behavioral adaptation are not included. This limits the analysis of certain levers that could help balance the

system, particularly in contexts with high shares of variable renewable energy [51].

Finally, some important dimensions of environmental sustainability are not accounted for. EnergyScope does not model emissions related to the construction of technologies (especially storage), nor those associated with the use of certain imported energy carriers such as renewable gases. This omission may lead to an underestimation of the actual environmental impact of the studied system.

These limitations explain why extensions to the model are often developed, such as the integration of uncertainty analysis or the inclusion of construction-related GWP, as presented in the following sections.

2.3 Energyscope TD model modifications

This section outlines the modifications made to the EnergyScope TD model as part of this work. These changes include: the integration of the global warming potentials associated with the construction of energy storage technologies, the shift in the optimization objective from cost minimization to GWP minimization, the addition of constraints on total system cost, as well as the management of energy imports.

These modifications were motivated by the desire to better represent the environmental challenges associated with the energy transition by 2050. The integration of GWP_{constr} for storage technologies helps capture environmental impacts that are often overlooked in conventional approaches, which focus primarily on the operational phase. The change in optimization objective from total cost minimization to greenhouse gas emission minimization reflects an exploratory approach centered on maximum decarbonization, regardless of economic constraints. Moreover, the addition of GWP_{op} for imported energy carriers prevents optimization biases that would externalize emissions beyond the modeled territory. Finally, a constraint on total system cost was introduced to ensure that the resulting environmental pathways remain both technically and economically realistic.

2.3.1 Objective shift: from cost minimization to emission minimization

In the standard configuration of EnergyScope TD, the energy system is optimized by minimizing the total annual cost, as shown in Equation (2.1). However, in this work, this objective was modified to prioritize the minimization of total greenhouse

gas emissions, measured via total GWP [53].

This total GWP consists of two main components: emissions associated with the construction of technologies and emissions related to the operation of energy resources.

$$\mathrm{GWP}_{\mathrm{tot}} = \sum_{j \in \mathrm{Technologies}} \left(\frac{\mathrm{GWP}_{\mathrm{constr}}[j]}{\mathrm{lifetime}[j]} \right) + \sum_{i \in \mathrm{Resources}} \mathrm{GWP}_{\mathrm{op}}[i] \tag{2.2}$$

where:

- $\mathrm{GWP}_{\mathrm{constr}}\ [j]$ represents the environmental impact associated with the construction of technology j, expressed in kt CO_2eq,
- lifetime$[j]$ is the lifetime of technology j,
- $\mathrm{GWP}_{\mathrm{op}}[i]$ corresponds to the operational emissions associated with resource i, expressed in kt CO_2eq/y.

This choice makes it possible to explore technological pathways that achieve maximum system decarbonization by 2050, regardless of economic considerations. It also reflects political carbon neutrality goals, which may justify environmental trade-offs at the expense of purely economic optimization.

2.3.2 Integration of global warming potentials related to the construction of storage technologies

To determine the GWP values associated with the construction phase of the energy storage technologies modeled in EnergyScope TD, several simplifying assumptions had to be made due to the lack of specific data. In many cases, the choices were made arbitrarily but remained consistent with the scientific literature or technological rationale. Additionally, some estimates were derived from calculations based on available data or relevant technological ratios; the details of these calculations are provided in Appendix A.1.

Assumptions

- The $\mathrm{GWP}_{\mathrm{constr}}$ of electric car batteries was assumed to be equivalent to that of lithium-ion batteries [43].
- Decentralized storage is modeled by a water tank in Energyscope TD's input data. [43]. According to the data sheet [40], the $\mathrm{GWP}_{\mathrm{constr}}$ is estimated at 5.62 kg CO_2eq/kWh.

- Daily thermal storage is modeled as a large-scale hot water tank system [43]. The GWP_{constr} is estimated using the same database as that used by EnergyScope TD, in order to ensure methodological consistency.
- Seasonal thermal storage is modeled in EnergyScope TD using Pit Thermal Energy Storage (PTES) system [43]. After unit conversion and appropriate adjustments, the estimated is 0.884 kg CO_2eq/kWh of storage capacity.
- Currently, high-temperature heat storage is not linked to any specific technology in EnergyScope TD. Due to the lack of detailed LCA data for such storage technologies, an initial estimate of the GWP_{constr} is proposed based on the highest value identified in a recent review of thermal energy storage systems.
  According to Wickramasinghe and Zhang [80], Sensible Heat Storage (SHS) systems can operate at temperatures up to 1 000 °C. The review compiles several case studies on technologies such as molten salt tanks and solid material beds. The highest GWP value reported in this document is adopted as a conservative initial assumption [80].
- Gas storage is modeled as salt caverns [43]. To estimate the GWP_{constr}, values reported for hydrogen storage in salt caverns were used. Since the global warming potential of construction primarily depends on the excavation and infrastructure rather than the type of gas stored, it is considered appropriate to use these values for other gaseous energy carriers [42].
- For fuel storage, no specific technology is assigned in EnergyScope TD. In practice [7, 31, 56] , fuels are predominantly stored in stainless steel tanks [74]. Based on a calculation using the material mass and its environmental impact, the GWP_{constr} is estimated at 5.7 g CO_2eq/kWh.
- For the storage of other fuels such as gasoline, Light Fuel Oil (LFO), ammonia and methanol, their GWP_{constr} was assumed to be equivalent to that of diesel, as they are also stored in liquid form in tanks [43].
- CO_2 storage in EnergyScope TD is neither an energy vector nor an energy storage technology. It is modeled as a technical carbon sink, similar to a forest capturing CO_2, but based on industrial infrastructure [43]. For this reason and due to its limited interaction with the energy system dynamics under study, this technology is not further analyzed in this work.

Global warming potential inserted in Energyscope TD

The global warming potential values for the construction of storage technologies used across all scenarios are presented in Table 2.1.

Technologies	Names in Energyscope TD	Values	
Batteries	BATT_LI	61.3	[26]
Batteries of electric cars	BEV_BATT	61.3	
Batteries of plug-in hybrid cars	PHEV_BATT	101	[47]
Pumped hydro storage	PHS	8.33	[26]
Decentralised direct elec	TS_DEC_DIRECT_ELEC	5.62	[40]
Dec. electrical heat pumps	TS_DEC_HP_ELEC	5.62	
Dec. thermal heat pumps gas	TS_DEC_THHP_GAS	5.62	
Dec. cogeneration gas	TS_DEC_COGEN_GAS	5.62	
Dec. cogen. oil	TS_DEC_COGEN_OIL	5.62	
Dec. fuel cell cogen. gas	TS_DEC_ADVCOGEN_GAS	5.62	
Dec. fuel cell cogen. H2	TS_DEC_ADVCOGEN_H2	5.62	
Dec. boiler gas	TS_DEC_BOILER_GAS	5.62	
Dec. boiler wood	TS_DEC_BOILER_WOOD	5.62	
Dec. boiler oil	TS_DEC_BOILER_OIL	5.62	
Centralised daily	TS_DHN_DAILY	37.2	[21]
Centralised seasonal	TS_DHN_SEASONAL	0.884	[65]
Thermal storage industries	TS_HIGH_TEMP	5.89	[80]
Gas storage	GAS_STORAGE	5.72	[42]
Hydrogen storage	H2_STORAGE	9.9	[79]
Diesel storage	DIESEL_STORAGE	0.0057	
Gasoline storage	GASOLINE_STORAGE	0.0057	
LFO storage	LFO_STORAGE	0.0057	
Ammonia storage	AMMONIA_STORAGE	0.0057	
Methanol storage	METHANOL_STORAGE	0.0057	
CO2 storage	CO2_STORAGE	0.005	[37]

Table 2.1: Global Warming Potential values in kg CO_2eq/kWh from the literature for the construction phase of the storage technologies considered in EnergyScope TD. All values are expressed per installed kilowatt-hour, not per kilowatt-hour used.

2.3.3 Cost constraint

Given Belgium's objective of achieving carbon neutrality by 2050 [66], the optimization of the energy system cannot be guided by purely economic considerations. The scenario selected in this study is therefore based on a level of investment high enough to reach near-zero greenhouse gas emissions.

Energy planning inherently involves conflicting objectives, particularly the minimization of economic costs and the reduction of greenhouse gas emissions. To assess the trade-offs between these goals, multi-objective analysis is commonly

used-one of its core concepts being Pareto optimality [35]. A solution is considered Pareto-optimal if no other solution improves one objective without worsening at least one other. The set of all such solutions forms what is known as the Pareto front [49, 83].

In this work, Pareto analysis is used to identify an upper bound on total cost when the system is optimized solely for emissions reduction. Setting the cost constraint equal to the economically optimal scenario would overconstrain the system, making convergence impossible. However, allowing the model to operate without any cost limit would lead to economically unfeasible outcomes. A balance must therefore be found: giving the model enough freedom to explore ambitious low-carbon solutions, while avoiding excessive costs for marginal gains in emissions reduction.

To achieve this, several simulations were carried out by gradually imposing annual cost restrictions ranging from 55 000 M€ to 100 000 M€, knowing that the cost of the unconstrained system was approximately 96 000 M€. Each point on the front was obtained using the so-called ϵ-constraint method [50, 54], which consists in fixing a maximum budget and minimizing the associated emissions. This approach generates a set of non-dominated solutions, mapping out the space of possible trade-offs between environmental and economic objectives.

The marginal cost [82] represents the amount of money that must be invested to avoid one additional tonne of CO_2. It is calculated as the ratio between the increase in total cost and the corresponding reduction in emissions:

$$\frac{\Delta \text{cost}}{\Delta \text{avoided emissions}} \tag{2.3}$$

This indicator allows us to assess, locally along the front, where decarbonization efforts remain reasonably affordable and where the trade-offs become economically unsustainable.

Figure 2.3 shows the resulting Pareto front and illustrates the evolution of the marginal abatement cost of CO_2 emissions along that front. This cost is plotted on a logarithmic scale to better visualize its sharp increase as the system approaches carbon neutrality.

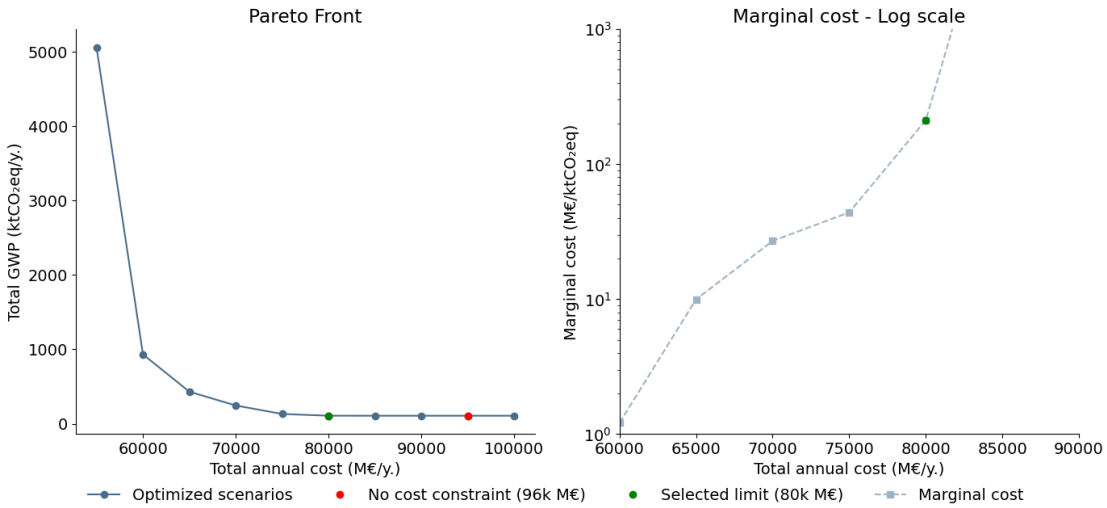


Figure 2.3: Trade-off between annual cost and emissions reduction of the energy system. Each blue point represents an optimized scenario. The red point corresponds to the scenario without any cost constraint, while the green point indicates the selected scenario with a cost constraint of 80 000 M€/y.

The results show a gradual increase in the marginal cost up to around 75 000 M€, followed by a steep jump beyond 80 000 M€, where it exceeds several hundred M€/kg CO_2eq. This discontinuity reflects a loss in decarbonization efficiency: beyond a certain threshold, each avoided ton of CO_2 requires disproportionately high investment. This phenomenon highlights the global behaviour of the energy system along the Pareto front. On the left side of the front, configurations are low-cost but highly emissive, relying on cheap yet carbon-intensive technologies. Conversely, configurations on the right side achieve very low emissions at the cost of much higher investments. The strong convexity of the front illustrates how environmental benefits become increasingly expensive as the system nears carbon neutrality. When represented on a logarithmic scale, this dynamic takes the form of a near-exponential cost growth, underscoring the steep financial burden of eliminating the final percentages of emissions.

To objectively select a relevant cost constraint, a numerical analysis was performed on the Pareto front results. A second derivative was estimated using the Savitzky-Golay filter [18] to identify the point of maximum curvature. The inflection point was found at 80 000 M€/y, corresponding to a total GWP of 108 kt CO_2eq/y. This value represents a meaningful compromise between climate ambition and economic feasibility and thus justifies the choice of the selected scenario, which achieves near-carbon neutrality.

2.3.4 Accounting for imports

Objectives

The initial simulations of the scenario aiming to minimize GWP emissions revealed a major shift in the energy system: local storage is almost entirely removed, electrification declines and dependence on imported energy vectors becomes substantial.

This result stems from a key assumption in EnergyScope TD: imported renewable resources are considered neutral in terms of GWP_{op}. However, such an assumption steers optimal trajectories toward externalized solutions, favoring the relocation of emissions rather than their effective reduction at the global scale.

To address this limitation and better represent the real climate impact of imported vectors, two complementary approaches were implemented:

- Direct reduction of the maximum availability of certain imported vectors by modifying the input files;
- Progressive increase of their GWP_{op}, to reflect their potential climate impact.

The first method, while limiting import flows, did not significantly alter the technological hierarchy of the system: technologies relying on these vectors remained favored. The second approach, more robust, was therefore preferred.

Method for adjusting GWP_{op}

An automated script was developed to gradually penalize imported resources by incrementally increasing their GWP_{op} at each iteration. After each simulation, the dominant energy resource, defined as the one with the highest energy contribution, is identified. If this resource is imported, its GWP_{op} is incremented by a constant step and a new simulation is launched. This process is repeated until a local resource becomes dominant, signaling a shift toward a domestic supply logic.

In this study, a structural tipping point is considered reached when the dominant technology is based on a local resource. This criterion marks a transition toward energy autonomy, even if some imports remain marginal. Full elimination of imports is not required, as such extreme scenarios do not necessarily reflect realistic transition pathways.

This procedure was applied exclusively to imported biofuel-type vectors, based on the following two criteria:

- Direct climate relevance: only resources that generate emissions during the usage phase are subject to penalization.
- Risk of emission relocation: only vectors assumed to be neutral in the model and produced outside the territory can lead to an artificial minimization of local emissions.

Other resources with zero GWP_{op} were left unchanged, for the following reasons:

- Local renewable vectors: their local production without combustion justifies a zero GWP_{op}.
- Carbon-related flows: these variables serve to balance the system's carbon accounting but are not energy carriers. Their GWP_{op} has no functional meaning.
- Electricity exports: this is an outgoing flow from the system. Its GWP is already accounted for in the corresponding production technology.

As for imported electricity, it is assumed to originate mainly from low-carbon sources, in line with European climate neutrality trajectories. Its GWP_{op} can therefore reasonably be considered zero or negligible in prospective scenarios. The associated emissions are more accurately represented in the construction phase of the relevant infrastructures, which are already included in the analysis. Moreover, its quantity is limited by explicit constraints in the model, preventing uncontrolled overreliance. This approach avoids penalizing a vector whose operational climate impact is indeed low by 2050.

Finally, certain imported resources, such as biodiesel and bioethanol, were never identified as dominant at the system scale. They are therefore not subject to the methodology described here. Their role will be examined more specifically in the section dedicated to mobility, where different technological or functional dynamics come into play.

Contributions of this method

The methodological adjustments outlined above enabled the definition of a corrected scenario, integrating a more realistic representation of the climate impact of imports.

This approach allows for the identification, for each concerned vector, of the GWP value beyond which it ceases to be favored by the model. These thresholds reveal strategic tipping points in the energy system. The resulting scenario then serves as a reference for sensitivity and uncertainty analyses, offering a more robust framework for the prospective assessment of transition pathways.

2.4 Technological transitions in storage and private mobility sectors

2.4.1 Objectives and scope of the analysis

This study places particular focus on technological transition dynamics in two key sectors: energy storage and private mobility. These sectors were selected due to their high sensitivity to assumptions regarding GWP and their critical role in the balance and resilience of the energy system by 2050.

Storage acts as a central vector of flexibility, enabling the integration of renewable energy and the management of peak demand. Private mobility, meanwhile, exhibits particularly pronounced technological substitution dynamics, characterized by rapid shifts between competing energy vectors.

The aim of this section is to systematically identify the environmental thresholds beyond which a given technology becomes non-competitive, or conversely, succeeds in dominating the optimized energy mix. The analysis seeks to evaluate the robustness of technologies under increasing environmental penalization, detect configurations that are highly sensitive to GWP assumptions and understand the substitution mechanisms between competing solutions.

2.4.2 Analytical definitions of technological transitions

This section introduces the analytical concepts used to characterize transition dynamics, particularly in the storage and private mobility sectors.

Tipping Point (TP)

The tipping point refers to the value of the GWP beyond which a technology ceases to be dominant in its sector [16, 46]. It reflects a structural shift in the system's balance and helps identify the strategic technologies to prioritize for decarbonization.

Reverse Tipping Point (RTP)

In contrast, the reverse tipping point corresponds to the GWP value at which a technology that was initially absent or marginal becomes dominant again. This concept allows for the analysis of both technology phase-outs and conditions under which technologies return to competitiveness.

Phase-Out Threshold (POT)

The phase-out threshold is defined as the GWP value beyond which a technology becomes so uncompetitive that it nearly disappears from the optimized energy mix [38]. It indicates an environmental limit beyond which the technology is systematically excluded.

Emergence Threshold (ET)

Conversely, the emergence threshold represents the GWP value at which a technology previously absent from the system succeeds in entering it. This concept helps assess whether environmental impact constitutes a major barrier to adoption, or if other techno-economic factors are at play.

2.4.3 Scenario used for the simulations

The scenario used in this section is based on the **Corrected Min gwp** scenario, developed during the analysis of import management. It incorporates GWP_{op} values for imported resources, as outlined in the methodology presented in Section 2.3.4.

However, certain imported resources such as biodiesel and bioethanol never appeared as dominant in the tested scenarios. As a result, they were not penalized in the initial analysis. To ensure fair treatment of all energy vectors, a complementary assumption is introduced in this section: an GWP_{op} value is assigned to these non-dominant resources, consistent with the values used for other imports. The details of this assumption are provided in the results section.

The modified scenario thus serves as the sole basis for all simulations in this section, including the analysis of disappearance and emergence thresholds, as well as direct and reverse tipping points.

Finally, some simulations obtained during the import management methodology are also used here to complement and enrich the results of this approach. This continuity ensures analytical consistency and leverages the full range of available data.

2.4.4 Analysis criteria and conventions

Several analytical conventions are adopted to ensure consistency and robustness in identifying technological transitions within the energy system.

Dominance criterion

A technology is considered dominant within a given category if its installed share is the highest among all competing technologies in that category for a given iteration.

Presence criterion in the mix

A technology is considered present in the energy mix if its installed capacity exceeds a minimal threshold of one unit. Conversely, it is deemed absent if its installed share falls below or equals this threshold. This convention helps filter out marginal effects and non-significant numerical fluctuations.

Stability criterion

The identification of a tipping point relies on the observation of a stable technological replacement. A tolerance threshold of several consecutive iterations is applied to ensure that the new dominant technology remains so over time. This rule avoids "yo-yo" effects between technology subgroups and ensures that the observed transition reflects a true structural reorganization of the system.

2.4.5 Simulation methodology

The methodology is based on a series of parametric analyses applied to the $\mathrm{GWP}_{\mathrm{constr}}$ of technologies. Values are modified in constant steps, each below 10 % of the reference value, to explore the sensitivity of technologies to increasing or decreasing environmental pressure. Two types of analysis are conducted separately: the study of disappearance thresholds and tipping points and the study of emergence thresholds and reverse tipping points.

Analysis of disappearance thresholds and tipping points

Two complementary approaches are implemented to characterize the trajectories by which technologies exit the energy mix. The first consists of tracking the system's evolution while progressively penalizing the dominant technology. At each iteration, its is $\mathrm{GWP}_{\mathrm{constr}}$ increased, forcing the model to reorganize the mix and bring a new dominant technology to the forefront. This process continues until all technologies have been dominant at least once or until no further structural changes are observed. In cases of cyclic replacement loops, the process is halted.

In parallel, a separate analysis is conducted for each technology individually. Its GWP value is gradually increased, while other technologies retain their reference values. The objective is to identify the threshold beyond which the technology is

no longer selected in the mix, thus evaluating its intrinsic environmental resilience. The combination of these two approaches allows for a cross-analysis of systemic substitution dynamics and targeted identification of eviction thresholds.

Analysis of emergence thresholds and reverse tipping points

This second analysis follows the inverse logic. It aims to identify the point at which a previously absent technology enters the system due to improved environmental performance. Starting from a GWP value initially too high to allow for selection, the value is gradually decreased, while the GWP values of other technologies remain unchanged. Two thresholds are sought: the emergence threshold, at which the technology enters the mix and the reverse tipping point, at which it becomes dominant.

The analysis is primarily applied to technologies that are absent in the initial scenario. When multiple candidates are present, the one with the highest GWP is selected first. This protocol helps distinguish environmental barriers from other potential adoption constraints of a techno-economic nature.

2.4.6 Sector-specific considerations

Storage

For the storage sector, the GWP_{constr} assumptions used in the simulations are identical to those defined in Section 2.3.2. However, in some cases, differentiated behaviors were observed between technologies sharing similar GWP values. To capture these specific dynamics, separate analyses were conducted for such technologies, despite the theoretical equality of their environmental parameters.

Private mobility

Mobility-related uses are classified into three distinct categories: private mobility, public mobility and freight transport. These needs are not substitutable in EnergyScope TD: a private mobility technology cannot satisfy public mobility demand. Nevertheless, indirect spillover effects may emerge, particularly in terms of pressure on certain resources or infrastructures. Special attention is paid to these interactions when interpreting the results.

To better understand the tipping dynamics in the private mobility sector, technologies have been grouped into coherent families, based on the nature of the energy vector used and the type of drivetrain. This grouping highlights major systemic transitions rather than minor substitutions between closely related

technologies. The classification is inspired by U.S. Environmental Protection Agency [76] and the selected families are as follows:

- **Biofuels:** gasoline, diesel, methanol and Natural Gas (NG) car
- **Hybrids:** Hybrid Electric Vehicle (HEV) and Plug-in Hybrid Electric Vehicle (PHEV)
- **Electric:** Battery Electric Vehicles (BEV)
- **Hydrogen:** Fuel Cell Electric Vehicles (FCEV)

Hybrid technologies are treated separately due to their dual energy dependency: they consume both electricity and fuels, which structurally differentiates them from purely thermal or purely electric drivetrains. They simultaneously rely on two separate supply chains: the electrical grid and imported fuel vectors.

GWP variations are applied simultaneously to all technologies within a given family. This method simulates coherent systemic evolutions, such as the introduction of a uniform environmental tax or a common methodological reassessment.

2.4.7 Methodological limitations

As with any parametric approach applied to a complex system, the methodology presented here has certain limitations that must be considered when interpreting the results. Two aspects, in particular, deserve to be highlighted: the stability of results under rapid alternation and the chosen level of granularity in the private mobility sector.

Technological instability effect

In some cases, progressively increasing the GWP of a dominant technology does not lead to a clear transition toward an alternative technology, but instead triggers repeated and rapid alternation between competing sub-families. This phenomenon, referred to here as a "yo-yo effect", renders the identification of a tipping point ambiguous.

When such behavior is observed from the early iterations, no technology clearly establishes dominance, making it impossible to define a robust tipping point. As a general rule, a transition is only validated if the new dominant technology remains so for a minimum number of consecutive iterations, as defined in Section 2.4.4. This safeguard ensures that conclusions are not drawn from transient fluctuations or unstable equilibria.

Granularity of analysis in private mobility

The analysis conducted in the private mobility sector is based on classification by technology families rather than individual technologies. This approach was chosen to better reflect broad energy transition dynamics and to account for structural interdependencies among technologies within the same family.

That said, this family-level granularity constitutes a simplification. It may obscure fine-grained differences between technologies within a category, especially when they exhibit distinct profiles in terms of emissions, costs, or operational flexibility. A more disaggregated complementary analysis could refine interpretations, provided that the induced interdependency effects are properly managed.

2.4.8 Relevance of the results obtained

The analysis of critical thresholds presented in this section goes beyond merely identifying limit values beyond which a technology becomes uncompetitive. It serves as a crucial complement to the stochastic analysis by offering targeted insight into the specific vulnerabilities of certain technologies and the substitution mechanisms that structure the energy system.

In particular, this approach improves the interpretation of correlations observed in the global sensitivity analysis by identifying the most decisive environmental parameters in optimized technology choices. It also reveals systemic links between storage, imports and mobility by highlighting intersectoral dependencies that can either reinforce or constrain system flexibility.

Beyond the technical analysis, these findings contribute to a broader reflection on the robustness of optimized transition pathways in the face of environmental uncertainties. They offer a relevant framework for guiding technological decarbonization decisions in the pursuit of carbon neutrality by 2050.

2.5 Methodology for validating co-variations between storage technologies

The analysis of co-variations between technologies was based on the full set of simulations previously used to identify tipping points and critical thresholds. Over 5 000 scenarios were generated as part of that process, involving directed variations in the $\mathrm{GWP}_{\mathrm{constr}}$ of key technologies, primarily in the storage and mobility sectors. These simulations were not designed as a random sample, but rather as a structured

exploration of the parametric space, aimed at uncovering transition dynamics.

Although the initial objective of these simulations was to identify appearance, disappearance and tipping thresholds, their volume and diversity also enable a broader analysis of systemic interdependencies. To this end, a comprehensive dictionary was built, storing the installed capacity of each technology across all scenarios.

When the GWP_{constr} of a given trigger technology is modified, the resulting changes in the installed capacity of other technologies can be tracked. By comparing these responses across all relevant scenarios, it becomes possible to compute, for each technology pair, the share of cases in which the capacity of a given technology increases, decreases, or remains unchanged in response to the trigger variation.

These shares should not be interpreted as statistical probabilities, but rather as trend indicators derived from a deterministic analysis. They allow the identification of substitution, complementarity, or partial independence relationships within the modeled energy system.

This approach serves to:

- reinforce transition patterns identified through threshold analysis by verifying their consistency across a wide range of contexts;
- uncover structural co-variation dynamics that may not be visible from individual tipping point trajectories;
- distinguish robust, system-wide relationships from more isolated or context-specific effects observed in individual scenarios.

In this respect, the co-variation analysis constitutes a natural extension of threshold-based investigations, offering complementary insights into the mechanisms of interaction and substitution between technologies.

2.6 Uncertainty and sensitivity analysis methodology with RHEIA

2.6.1 Objectives

By 2050, significant uncertainties remain regarding the techno-environmental data used in energy system models. Among these, the objective of this section

is to analyze to what extent such uncertainties influence the results of the EnergyScope TD model, particularly in terms of optimized technological pathways and the trade-offs between environmental and economic criteria.

In this work, the uncertainty analysis mainly focuses on the GWP_{constr} of certain technological families, such as energy storage systems or vehicles. The choice of parameters is based on their strategic relevance in the studied scenarios.

To carry out this analysis, the Robust design optimization of renewable Hydrogen and dErIved energy cArrier systems (RHEIA) tool was used. This simulation framework quantifies the impact of uncertainty on model outputs by generating a large number of scenarios through random sampling. Although RHEIA also provides robust optimization features, only its uncertainty propagation capabilities are used here [67].

Unlike classical parametric approaches, where one parameter is modified at a time in a deterministic fashion, the method adopted here relies on simultaneous exploration of multiple uncertain parameters. These are defined using probability distributions and then propagated through successive simulations of the EnergyScope TD model. This approach makes it possible to assess the robustness of the results obtained in previous scenarios and to identify the most influential parameters affecting the technological trajectories.

2.6.2 Inputs: definition of design and stochastic spaces

The uncertainty analysis carried out with RHEIA is based on the distinction between deterministic and uncertain model parameters. A model parameter may refer either to a fixed input or to a variable with unknown future evolution [67].

To structure this distinction, RHEIA uses two complementary input files: the `design space` and the `stochastic space`.

Design space

The design space contains the reference values assigned to each studied parameter. These values correspond to the assumptions used in deterministic simulations, i.e., in the absence of uncertainty [67].

Stochastic space

The stochastic space defines the potential variability of the parameters listed in the design space. For each parameter considered uncertain, the following must be specified:

- the type of probability distribution (uniform or Gaussian);
- the type of uncertainty (absolute or relative);
- the deviation from the mean value.

When the distribution is uniform, the deviation refers to the distance between the mean and the upper bound. For a Gaussian distribution, it corresponds to the standard deviation. Any parameter included in the design space but not mentioned in the stochastic space is automatically treated as deterministic [67].

Global analysis settings

The user also defines a set of global parameters for the analysis, including the maximum polynomial order for the expansion and the model output selected as the quantity of interest. By default, the sampling method used is the Sobol sequence [67].

This configuration enables efficient propagation of uncertainties through the EnergyScope TD model and facilitates analysis of their effects on technological trajectories and global performance indicators.

2.6.3 Outputs : statistical and sensitivity analysis

Once the Polynomial Chaos Expansion is constructed, RHEIA automatically generates a set of statistical indicators and visualizations to assess the effects of uncertainty on model outputs. These results provide both a global view of the output variability and a sensitivity analysis of the uncertain parameters.

The main outputs are [67]:

- Mean and standard deviation: these indicators characterize the central tendency and dispersion of the model outputs.
- Probability Density Function (PDF): this provides a continuous visualization of the probability associated with each possible value of the output of interest, revealing the structure of uncertainty.

- Sobol indices: these quantify the contribution of each uncertain parameter to the variance of the model output. RHEIA provides both first-order and second-order indices, enabling a comprehensive sensitivity analysis.
- Leave-One-Out (LOO) error: this indicator assesses the quality of the PCE metamodel. A low LOO error indicates that the PCE accurately replicates the behavior of the original model [48].

In addition, RHEIA can generate PDF and Cumulative Density Function (CDF) distributions using a Monte Carlo evaluation of the metamodel. In this study, 100 000 samples were used for this step, allowing for smoothed, statistically robust distributions at negligible computational cost compared to direct simulations of the original model [67].

2.6.4 Model explanation

In this study, the RHEIA software is used exclusively for uncertainty quantification, without leveraging its multi-objective optimization capabilities such as Non-Dominated Sorting Genetic Algorithm 2 (NSGA-II) [20]. The aim is to evaluate how uncertainties in certain technological parameters influence the results of the EnergyScope TD model by 2050.

The approach used in this work follows a methodology taught in the Robust Optimization of Energy Systems course [35], using the RHEIA tool already coupled with EnergyScope TD.

The methodology used for uncertainty quantification is based on four main steps, summarized in Figure 2.4. This procedure is implemented via RHEIA and relies on the use of a Sobol sequence to generate representative samples from the uncertainty space.

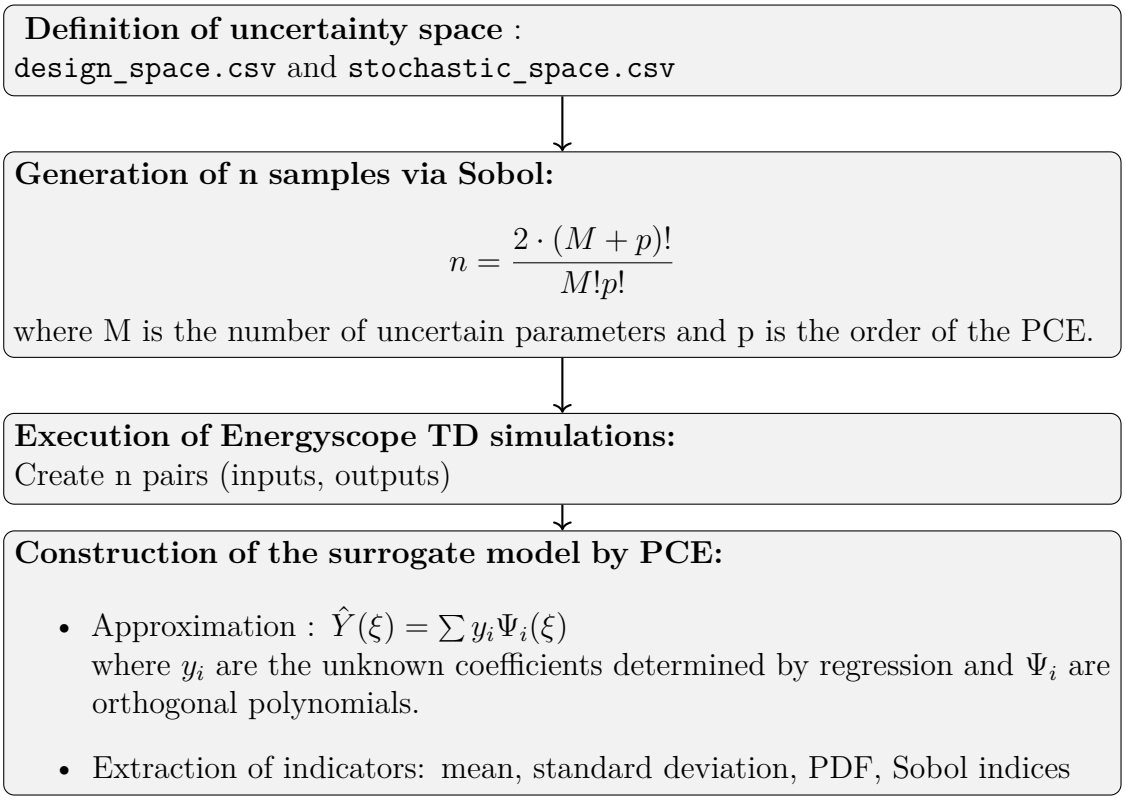


Figure 2.4: Workflow of the stochastic analysis using RHEIA, applied to the EnergyScope TD model. After defining the uncertain parameters and target outputs, a Sobol sampling plan is generated. Each sample triggers a full simulation and the results are used to build a surrogate model via PCE, from which statistical indicators such as the mean, standard deviation, PDF and Sobol indices are extracted.

After defining the uncertain parameters and their probability distributions, a set of n combinations is generated. Each sample corresponds to a full simulation of EnergyScope TD. The results obtained are then used to build a metamodel based on PCE, which provides an analytical approximation of the model outputs.

This metamodel is then used to estimate the statistical moments of the outputs, identify the most influential parameters using Sobol indices and generate the PDF and CDF curves.

2.6.5 Modifications and applications in this work

The stochastic analyses carried out in this work focused exclusively on evaluating the impact of uncertainty on the total GWP, in line with the emission minimization

objective. All parameters considered uncertain were assigned a relative uncertainty of 20 %, in accordance with the recommendation of Moret [54], who considers this level representative of moderate technological uncertainty in the absence of more specific data. Due to insufficient data to accurately characterise probability distributions, the assumption retained, in line with Rixhon [68], is that uncertain parameters follow a uniform distribution, which leads to a stochastic-type implementation.

The construction of the metamodel using PCE starts with a polynomial order of $p = 1$. The resulting model is evaluated using the LOO error. If this error remains below 1 %, the corresponding polynomial order is considered sufficient to accurately capture the model's behaviour [69].

This methodology was applied to the analysis of energy storage technologies and the private mobility sector. The detailed results are presented in the corresponding sections of the next chapter.

2.7 Structuring of analysis scenarios

The assumptions specific to each scenario are detailed in Table 2.2, while their logical sequence is illustrated in Figure 2.5. These two figures serve as the guiding framework for the approach adopted in this master thesis.

To investigate the impact of GWP on the technological choices of the energy system, a series of scenarios was progressively constructed. Each scenario introduces an additional constraint or assumption compared with the previous one, making it easier to isolate the specific effects of taking into account embodied emissions, particularly those associated with storage technologies and imported vectors.

Scenarios	Assumptions	Sections
Reference	Cost minimisation under a GWP constraint set at 10 Mt CO_2eq/y.	Section 3.1 Section 3.2 Section 3.3
Min gwp	Minimisation of total GWP under a cost constraint set at 80 000 M€, including the GWP_{constr} of storage construction.	Section 3.2 Section 3.3
Min gwp corrected	Addition of GWP_{op} for dominant imported renewable energy carriers, correcting the bias in favour of imports.	Section 3.3 Section 3.4
Threshold scenario	Addition of a GWP_{op} value for non-dominant imported vectors to ensure equity. Used as a base for threshold and tipping point analyses.	Section 3.5 Section 3.6

Table 2.2: Summary of the assumptions defining the analysed scenarios. Each scenario introduces an additional constraint or hypothesis, enabling a step-by-step assessment of the impact of embodied emissions related to storage technologies and imported energy carriers. The corresponding sections indicate where the results are discussed.

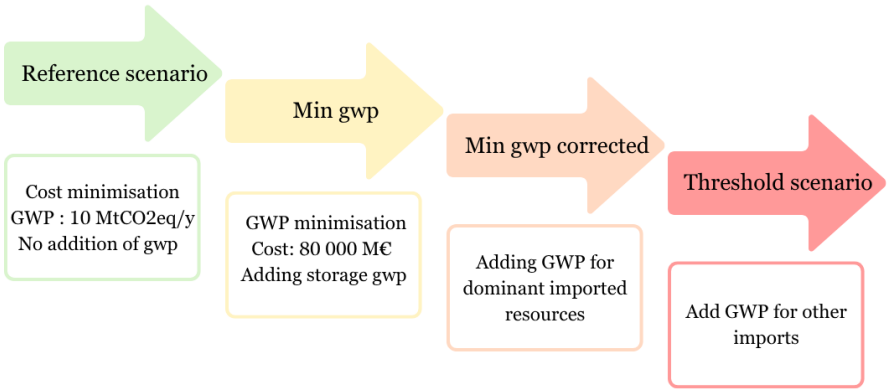


Figure 2.5: Schematic representation of the sequential construction of scenarios. Starting from a reference case based on cost minimisation under an environmental constraint, each subsequent scenario adds a new layer of GWP consideration from storage technologies to dominant and then non-dominant, imported energy vectors. This progressive structure forms the basis for threshold and tipping point analyses.

This stepwise structuring enables the comparison of optimization outcomes under different objectives, the identification of biases resulting from the absence of GWP values for certain imported vectors and the establishment of a robust foundation for the analysis of critical thresholds, tipping points and uncertainty. The final scenario, referred to as the **Threshold scenario**, serves as the primary methodological reference for all parametric analyses conducted throughout this master thesis.

Chapter 3

Results and analysis

This chapter presents and analyzes the results obtained from simulations carried out with the EnergyScope TD model for Belgium in 2050. The explored scenarios explicitly integrate the GWP_{constr} of energy storage technologies, as well as their uncertainties, in order to assess their influence on the optimal configuration of the energy system. After a concise reminder of the key parameters and assumptions adopted, the results are organized into several main themes: the effects of incorporating GWP_{constr} on optimized trajectories, the identification of technological tipping points, intersectoral interactions (storage, mobility, imports) and stochastic analyses. The objective is to highlight, for each theme, the structural trends, the induced trade-offs and the implications for long-term energy planning.

3.1 Reference scenario: description of the optimal energy system by 2050

The reference scenario outlines a transition pathway for Belgium's energy system by 2050, incorporating realistic climate targets, representative economic constraints and partial availability of energy imports. This scenario serves as a benchmark for assessing the impact of uncertainties and environmental constraints on future technological choices.

According to estimates from the federal long-term strategy [11], Belgium's total greenhouse gas emissions in 2050 could range between 10.2 Mt CO_2eq and 12 Mt CO_2eq. The emissions limit in the reference scenario is thus set at 10 Mt CO_2eq, ensuring a consistent level of ambition while accounting for the limited scope of the EnergyScope TD model, which excludes certain sectors such as agriculture.

This scenario is based on large-scale electrification, intensive deployment of renewable energy and system flexibility ensured through storage and imported

synthetic energy carriers.

3.1.1 Global indicators of the reference scenario

Table 3.1 presents the main indicators of the reference scenario by 2050. These figures provide a concise overview of the optimized energy system in terms of GHG emissions, economic costs and structural characteristics.

Emissions	
Construction phase	5 675 kt CO_2eq
Operation phase	4 324 kt CO_2eq
Cost	
Investment (C_{inv})	24 510 M€
Maintenance (C_{maint})	5 796 M€
Operation (C_{op})	19 132 M€
Total system cost (C_{tot})	49 438 M€
System Characteristics	
Imported energy share	50 %
Storage utilization	40 TW h

Electrification Rates	
High temperature heat	70 %
Low temperature heat	100 %
Public mobility	80 %
Private mobility	100 %
Freight mobility	9 %
Storage	2 %

Table 3.1: Key indicators of the reference scenario in 2050. Cost and emission values are expressed on an annual basis for the year 2050. The electrification rate of storage refers to technologies operating exclusively with electricity as input.

From an environmental perspective, GHG emissions are relatively evenly distributed, with 57 % attributed to the construction phase. This significant share highlights the non-negligible role of material choices, infrastructure and deployed technologies. It is therefore essential to complement this estimate with a more comprehensive LCA, particularly by incorporating components still absent from the model.

From an economic standpoint, the total system cost amounts to nearly 50 000 M€, with approximately half stemming from initial investments. This budget structure reflects a strategy focused on large-scale infrastructure, consistent with the high level of electrification observed across several sectors.

The analysis of structural characteristics reveals an energy dependency on external sources, with imports accounting for 50 %. This vulnerability primarily concerns renewable synthetic fuels, whose future availability may be subject to geopolitical or logistical uncertainties. Storage provides an important lever for system flexibility but remains undersized to ensure true energy autonomy.

Finally, sectoral electrification rates reveal clear strategic choices: low-temperature heat, private mobility and high-temperature heating exhibit high electrification levels, reflecting a strong intent to replace fossil fuels with low-carbon electricity. In contrast, freight transport and storage remain weakly electrified, underscoring the technological or economic challenges of large-scale electrification in these sectors.

3.1.2 Breakdown of environmental and economic impacts

To better understand the origin of the global indicators, this section details the distribution of GHG emissions as well as investment, maintenance and operation costs by technology category and by resource.

Global warming potential: construction vs operation

Figure 3.1 compares the distribution of greenhouse gas emissions between the construction phase of technologies and the operational phase of resource use. Emissions from construction are largely dominated by the electricity sector. This concentration is explained by the significant investments in renewable infrastructure, which require materials with a high carbon footprint [72].

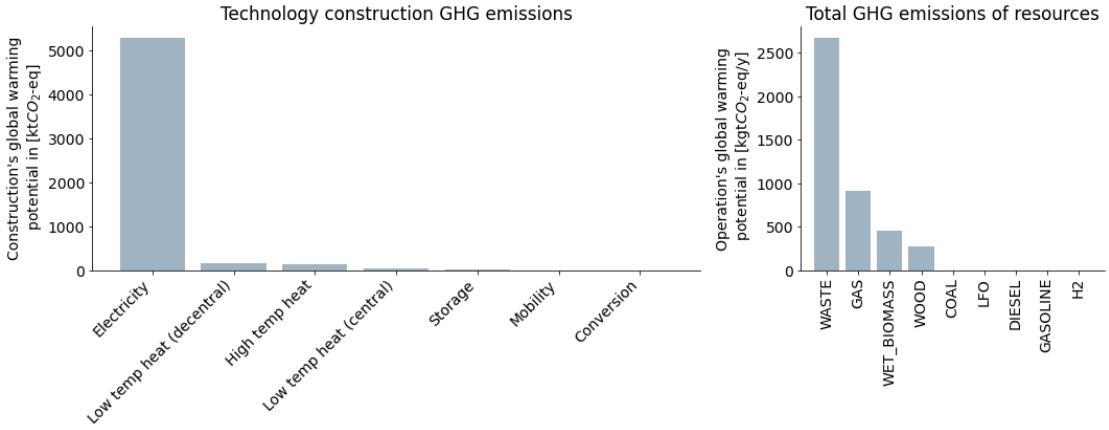


Figure 3.1: Visualization of the origin of greenhouse gas emissions in the reference scenario: on the left, emissions from the construction of technologies, mainly concentrated in the electricity sector; on the right, emissions from resource combustion, dominated by waste and natural gas.

In the operational phase, emissions are mainly caused by the combustion of waste, natural gas and wet biomass. Although some of these resources are partially renewable, they still have a significant environmental impact due to direct combustion [43]. The use of conventional fossil fuels is absent from the energy mix,

in line with the carbon neutrality objectives set for 2050.

Other sectors remain marginal contributors. This is notably the case for mobility and storage, which appear weakly represented in the carbon footprint. However, this low contribution does not necessarily reflect exemplary environmental performance: only Li-ion storage and pumped hydro technologies have GWP values specified in EnergyScope TD. Similarly, mobility technologies currently include no $\text{GWP}_{\text{constr}}$ data in the model's database. The lack of data for other storage technologies and transport infrastructure introduces a bias that likely underestimates their true impact. This methodological limitation highlights the need to enrich the life cycle assessment databases integrated into energy system modelling tools.

Distribution of energy system costs

Figure 3.2 illustrates the structure of energy system costs in the reference scenario, broken down into three complementary components. Capital expenditures are mostly concentrated in the mobility and electricity sectors, reflecting an ambitious electrification strategy based on the large-scale deployment of decarbonized vehicles and renewable electricity generation. This trend is echoed in the annual maintenance costs, which are largely driven by the upkeep of the electrified mobility fleet, underlining the structural importance of this sector in the energy system's economy.

In parallel, operational costs are strongly linked to the use of imported energy carriers. Renewable synthetic fuels constitute the main sources of expenditure due to their high costs despite their low carbon intensity. Electricity, although partially produced domestically, also incurs significant import-related expenses.

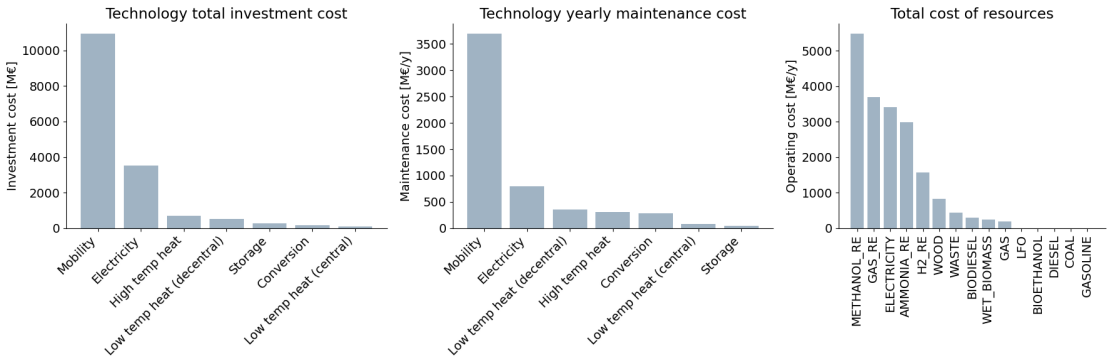


Figure 3.2: Cost breakdown of the reference scenario in 2050. Investment and maintenance costs are dominated by the mobility and electricity sectors. Operating costs are concentrated on imported energy carriers, mainly renewable.

This reliance on imported energy carriers with high operational costs raises questions about system resilience. Indeed, such flows are potentially vulnerable to geopolitical, logistical, or economic disruptions, which could undermine the robustness of the energy system.

In contrast, storage appears as a low-cost component in terms of operation, despite its strategic role in system flexibility. This makes it a relevant resilience lever that should be further developed.

Final resource consumption

Figure 3.3 shows the breakdown of energy resources used, expressed in terms of primary energy. A clear predominance of local renewable carriers,mainly solar and wind, can be observed, closely followed by imported renewable synthetic fuels such as methanol and ammonia. These play a central role in the system's energy supply, reflecting a clear orientation toward decarbonization through the import of low-GHG energy carriers. In parallel, several carbon-based resources are still present in the mix, such as natural gas, wet biomass, waste and wood.

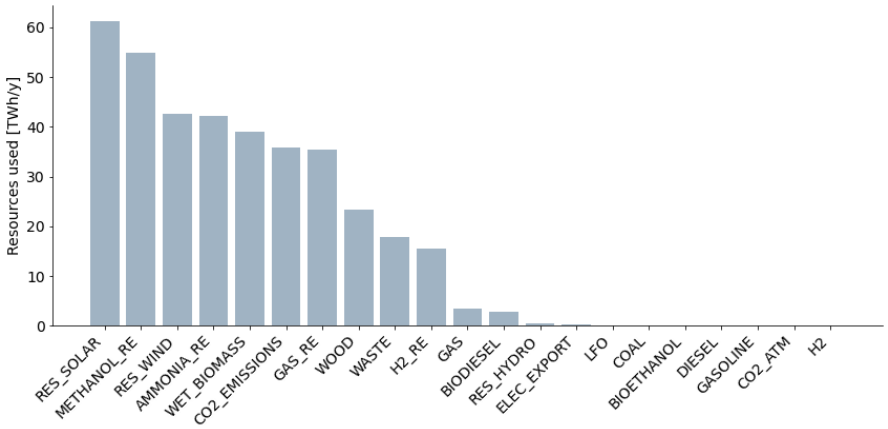


Figure 3.3: Use of primary energy resources in the reference scenario by 2050, expressed in annual energy [$\mathrm{TW\,h\,y^{-1}}$]. Local renewable resources dominate, but imported synthetic fuels also represent a significant share, reflecting a partial outsourcing of environmental impact.

The import of renewable synthetic carriers represents a strategy of outsourcing environmental impacts beyond national borders. These fuels emit little during their use phase, but their upstream production can result in significant emissions if it relies on processes that are not fully decarbonized.

3.1.3 Optimal technological choices

This section provides a detailed analysis of the technologies selected by the model to meet energy demand while complying with environmental and economic constraints.

Production: dominance of solar in electricity and electrification of heat

Figure 3.4 illustrates the installed capacities required to meet the demand for electricity as well as for high- and low-temperature heat. The electricity system is overwhelmingly dominated by intermittent renewable sources, particularly PV solar and onshore wind.

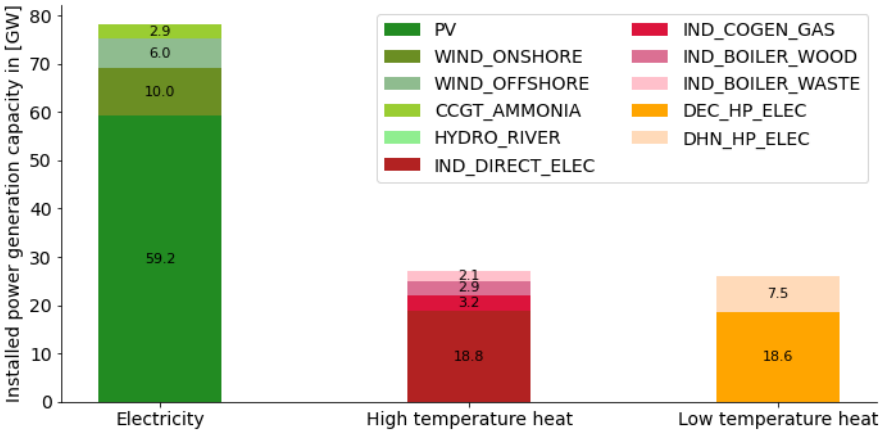


Figure 3.4: Optimal installed capacities for power generation, high-temperature process heat and low-temperature heat, expressed in GW. Electricity production is dominated by photovoltaic panels, while heat production is mainly electrified.

For high-temperature heat demand, the mix relies on large-scale electrification. This technological choice reflects a clear intention to decarbonize heavy industry by replacing fossil-fuel boilers with electric or biomass-based solutions.

Low-temperature heat is primarily supplied by heat pumps, both decentralized and centralized via district heating networks. This confirms the full electrification of this segment of thermal demand, historically dominated by gas [44].

This mix thus reflects a massive electrification of end uses, supported by a high penetration of intermittent renewables, which in turn implies a significant need for storage and flexibility.

Energy storage: key role of seasonal thermal and gas-based solutions

Figure 3.5 presents the installed capacities for various forms of energy storage, distinguishing between electrical, thermal and chemical storage.

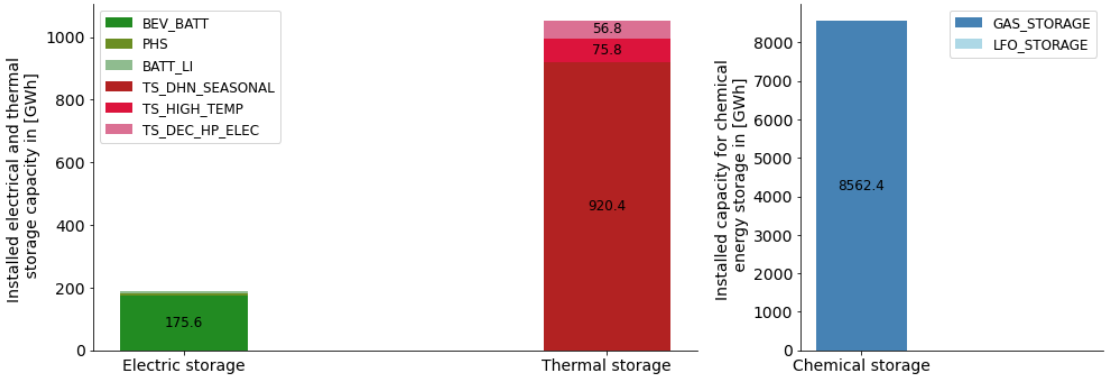


Figure 3.5: Optimal installed storage capacities by vector: electrical, thermal and chemical, expressed in GW h. Gas storage largely dominates biofuel storage, seasonal storage is predominant for heat storage and batteries manage electrical storage.

Thermal storage plays a central role in the system's flexibility, with a clear predominance of seasonal storage for district heating networks. It is complemented by shorter-term solutions such as high-temperature storage for industrial needs.

Electrical storage is more limited in volume and relies almost exclusively on electric vehicle batteries, highlighting the strategic importance of integrating concepts such as V2G.

Finally, synthetic gas storage is developed at a significant scale. It functions as a seasonal buffer and provides a flexible energy reserve that can be mobilized during demand peaks or periods of low renewable production.

Thus, the flexibility strategy is mainly based on three pillars:

- Seasonal thermal storage to ensure continuity in heat supply.
- Electric vehicle batteries for short-term and cross-sectoral flexibility.
- Chemical storage in the form of gas acting as a large-scale energy backup.

Mobility: electrification of private transport and partial decarbonization of freight

Figure 3.6 shows the distribution of transport technologies across passenger mobility and freight transport sectors. It reveals an almost complete electrification of private mobility, largely achieved through BEV.

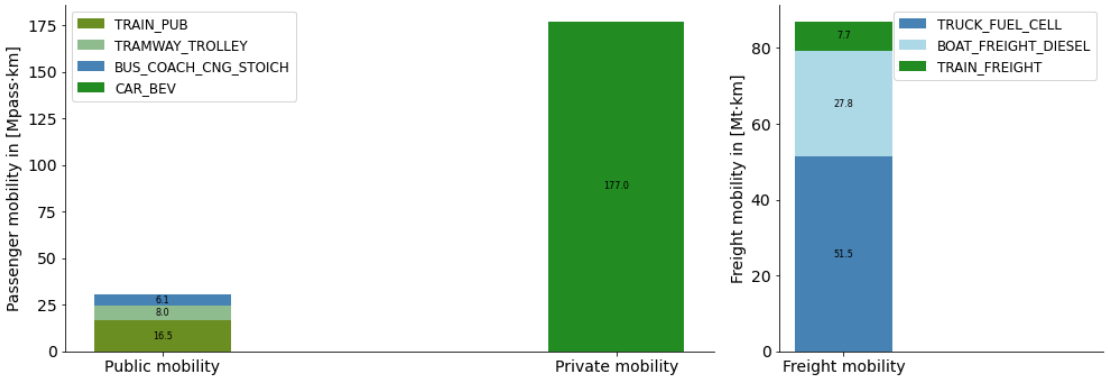


Figure 3.6: Breakdown of mobility demand by technology used, expressed in Mpkm for passenger mobility and in Mt km for freight mobility. Private mobility is dominated by BEV, public mobility by trains and freight transport by Fuel Cell Electric Trucks (FCET).

Public transport remains more diverse through the coexistence of trains, trams and gas-powered buses. However, their overall share in passenger mobility remains limited, highlighting an underexploited potential for large-scale decarbonization.

Regarding freight transport, hydrogen trucks are the dominant technology. Rail transport remains modest, despite its advantages in terms of energy efficiency and low emissions.

This logistical profile reveals a persistent dependence on non-electric energy carriers, whose usage-phase emissions strongly depend on the production process and country of origin. Such dependence could undermine emission reduction efforts if these fuels are not strictly produced from certified low-carbon sources.

3.1.4 Key dynamics of the energy system

The optimized scenario highlights a largely electrified energy system, structured around solar, wind and heat pumps. Electrification is particularly pronounced in the residential, industrial and private mobility sectors. In parallel, system flexibility relies on a triptych: seasonal thermal storage, vehicle batteries and synthetic gas. Despite this advanced decarbonization, the system retains a degree of dependence on certain imported carriers and residual carbon-based resources.

3.2 Scenario comparison

This section compares three optimization scenarios for the Belgian energy system by 2050, each defined by specific objectives and environmental constraints:

- **Ref:** the reference scenario introduced in Section 3.1.
- **Min cost:** the reference scenario with the addition of the $\text{GWP}_{\text{constr}}$ of storage technologies.
- **Min gwp:** a scenario aiming to minimize total emissions under a cost constraint, as justified in Section 2.3.3.

The goal is to assess how accounting for the GWP of storage infrastructures influences the optimal trajectories of the energy system. The analysis focuses successively on the evolution of storage technologies, sectoral technological reconfigurations, primary resources mobilized and finally the overall impact on key system indicators.

This framework allows for evaluating to what extent these new environmental constraints alter the technical and economic balances and what systemic dynamics emerge as a result.

3.2.1 Evolution of energy storage

Figure 3.7 illustrates the evolution of installed capacities for storage technologies across the alternative scenarios. While certain trends are shared, the trajectories diverge significantly depending on the pursued objective.

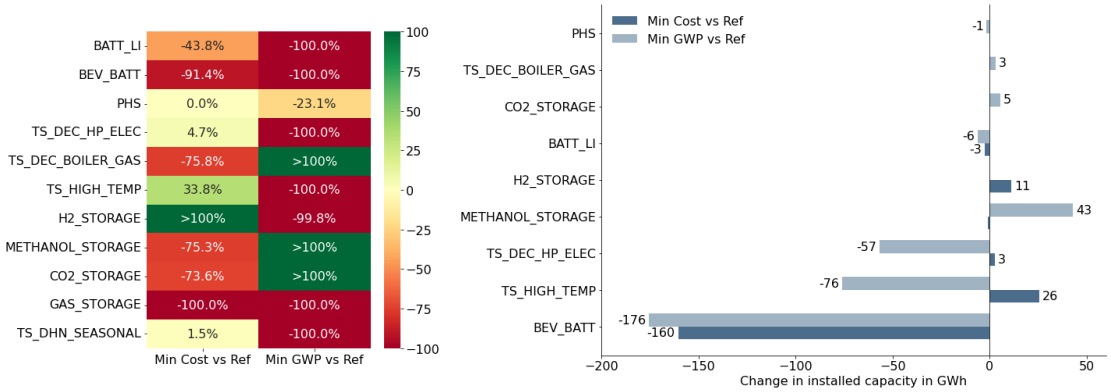


Figure 3.7: Relative in % and absolute in GW h change in installed storage capacities in 2050 for the **Min cost** and **Min gwp** scenarios compared to the reference scenario. Left: relative variation in percentage, with a color scale from red (strong decrease) to green (strong increase). Right: absolute variation in GW h, highlighting the magnitude of installed capacity changes for each storage technology.

A major finding lies in the disappearance of gas storage. In the reference scenario, it played a key role in meeting peak demand, in connection with cogeneration. However, in the alternative scenarios, cogeneration is abandoned and gas is only used for low-flexibility applications. Gas becomes a rigid vector and its storage loses all economic and environmental value.

Batteries also experience a significant decline, even a complete elimination in the total GWP minimization scenario. The shift towards FCEV, perceived as less emissive, marginalizes BEV. This substitution is driven by the model assumption that imported renewable vectors have no GWP_{op}.

Hydrogen storage evolves in contrasting ways: it intensifies in the **Min cost** scenario, where it supports hydrogen imports by providing local flexibility. In contrast, it disappears in **Min gwp**, where hydrogen is imported in the form of ammonia and only converted locally at the point of use, thus avoiding the need for pressurized storage infrastructure.

Thermal storage also varies: that associated with heat pumps and seasonal heat storage remains stable in **Min cost**, but collapses in **Min gwp**, which de-electrifies part of the system. Conversely, storage linked to gas boilers and methanol declines in **Min cost**, but reappears locally in **Min gwp**, reflecting increased reliance on imported vectors.

Some technologies remain largely unchanged. Pumped hydro storage remains stable, as its GWP_{constr} is already accounted for in EnergyScope TD, as is the case for lithium batteries. The latter exhibit large relative variations, but on low absolute volumes, thus limiting their structural impact.

These observations highlight how sensitive the role of storage is to the pursued objectives. In a cost-driven logic, the system strengthens local flexibility through storage. In contrast, under a GWP minimization logic, storage is reduced or even eliminated and flexibility is ensured by imported vectors that are converted on demand.

3.2.2 Technological reallocation and resource allocation

Table 3.2 on dominant technologies by sector and Figure 3.8 on resource use highlight the systemic repercussions of these strategies.

Sectors	**REF**	**MIN COST**	**MIN GWP**
ELEC	PV	=	CCGT
HEAT HT	Electricity	↗ Electricity	Boiler gas
HEAT LT	HP ELEC	=	Boiler gas
Private mobility	BEV	FCEV	↗ FCEV
Public mobility	Train	=	Biogas Bus
Freight mobility	FCET	=	↗ FCET
Storage	Gas Sto.	Seasonal Sto.	Methanol Sto.
Conversion	Methanol → HVC	=	Ammonia → H_2

Table 3.2: Dominant technologies selected by the model in the three analysed scenarios. For a more comprehensive view of technological dynamics, the top 3 technologies by sector for each scenario are detailed in Appendix B. The **Min gwp** scenario changes radically and favours the use of biofuels.

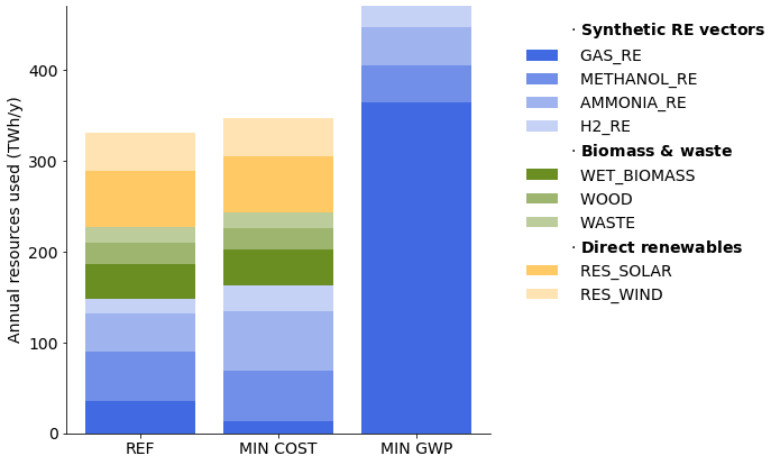


Figure 3.8: Annual use of renewable resources in 2050 for the REF, Min Cost and Min GWP scenarios. Stacked bars distinguish synthetic renewable vectors (blue), biomass and waste (green) and direct renewables (yellow). Across the scenarios, imports progressively increase until they account for the entire energy system. At the same time, the consumption of primary resources rises, indicating an overall decline in energy efficiency.

The **Ref** and **Min cost** scenarios retain a relatively stable structure, characterized by strong electrification, a balanced mix of local resources and moderate reliance on synthetic vectors. The introduction of $\mathrm{GWP}_{\mathrm{constr}}$ for storage technologies results in only marginal adjustments, with the main technological balances being preserved.

In contrast, the **Min gwp** scenario stands out clearly. The system shifts toward solutions with lower emissions during the construction phase, even at the expense of partial de-electrification. Heat Pump (HP) are replaced by gas boilers, PV is substituted by CCGT and imported synthetic vectors become predominant, particularly in the mobility sector. This heavy use of gas, ammonia and methanol reflects a strategy of outsourcing the GWP: emissions associated with the exploitation of imported renewable resources are not accounted for in the model. However, this shift comes at the cost of decreasing overall efficiency, as the system requires increasingly large amounts of primary resources to meet the same final energy demand.

3.2.3 Overall system impacts

Table 3.3 summarizes the effects of the two alternative scenarios compared to the reference scenario.

In the **Min cost** scenario, FCEV replace BEV, which increases investment costs; storage reorganizes around high-temperature heat; and imports increase slightly. Electrification remains generally stable and flexibility continues to be largely ensured by local solutions.

Indicators	**Min Cost**	**Causes**	**Min GWP**	**Causes**
Total cost	+ 6.7 %	C_{inv} ↗	+ 62 %	Cost limit
Total GWP	=	GWP limit	− 98.9 %	Externalisation
Imports	+ 6.6 %	Ammonia as main resource	+ 170 %	Externalisation
Storage	+ 8.8 %	↗ Sto. heat HT	− 97 %	Electrification ↘↘
Electrification	↘ Private mobility	BEV → fuel cell	all ↘↘	Externalisation

Table 3.3: Changes in key indicators of the alternative scenarios compared to the reference scenario. Percentages indicate relative variations, while the right-hand columns specify the main identified causes for each indicator.

In contrast, the **Min gwp** scenario leads to a radical transformation of the system. Local emissions collapse but this reduction relies almost entirely on massive outsourcing. Local storage is eliminated, electrification declines sharply and imports surge to provide both flexibility and energy supply.

Conclusion

Including $\text{GWP}_{\text{constr}}$ in the simulations alters the optimal energy system trajectories, though in highly contrasting ways depending on the pursued objective.

In the **Min cost** scenario, adjustments remain limited. The system maintains strong electrification and storage is adapted locally to meet the new constraints.

The **Min gwp** scenario, however, triggers a structural transformation: local storage disappears, electrification declines and flexibility relies almost entirely on the import of synthetic vectors. This strategy hinges on a key model assumption:

the GWP_{op} of imported vectors is considered zero [43]. This leads to a massive outsourcing of emissions, without any actual global reduction.

This bias highlights a major limitation of the current modeling framework: as long as upstream impacts of imports are not accounted for, the system will favor deceptively optimal trajectories. It is therefore essential to revise this assumption to ensure the climate robustness of the results.

This comparison also reveals that storage plays a central role in system balance: it is either reinforced to provide local flexibility or eliminated when environmental constraints become too stringent. It acts as a strategic adjustment variable in the trade-off between cost, emissions and import dependency.

Finally, the analysis highlights pronounced threshold effects: slight variations in parameters can trigger rapid technological shifts, or even complete reversals.

For this reason, the following sections focus on the analysis of uncertainties, tipping points and disappearance thresholds affecting storage technologies, import management and mobility choices.

3.3 Effects of accounting for imports

3.3.1 Issue and objective

The **Min gwp** scenario, designed to minimize territorial emissions by 2050, paradoxically leads to a highly externalized energy pathway: imported vectors provide most of the system's flexibility, local storage is phased out and electrification declines in several sectors. This drift stems from a simplifying assumption: imported resources are considered neutral in terms of GWP_{op}. This assumption biases the model's techno-economic trade-offs by overly favoring imports.

This section aims to show how correcting this assumption leads to structural transformations in the energy system, without conducting a full scenario comparison. The modified scenario, in which imported vectors are progressively penalized based on their GWP_{op}, is referred to hereafter as **Min gwp corrected** .

3.3.2 Methodology and selected values

As presented in Section 2.3.4, an algorithmic loop was used to progressively adjust the GWP_{op} of imported resources. At each iteration, the dominant resource was identified and penalized if it was imported, until a local resource took over. This transition marks a structural tipping point, interpreted as a fundamental shift in the supply logic.

The resulting GWP_{op} values are presented in Table 3.4. These values are consistent with literature data, notably Rai et al. [64], who estimates the GWP_{op} of renewable gases at 0.097 kg CO_2eq/kWh.

Imported vector	GWP_{op} (kg CO_2eq/kWh)
Renewable gas	0.10
Renewable hydrogen	0.09
Renewable ammonia	0.07
Renewable methanol	0.11

Table 3.4: GWP_{op} values assigned to imported energy carriers in the corrected scenario. These values reflect the upstream emissions associated with each dominant imported renewable energy source. Only the main carriers are considered here; other imported renewable vectors, such as bioethanol and biodiesel, are addressed in Section 3.5.1.

3.3.3 Transformation of technological balances and systemic changes

Return of electrification

When imported vectors are no longer considered environmentally neutral, the model once again favors local solutions. Heat pumps become competitive again for low-temperature heat and electricity regains a significant role in high-temperature industrial applications. In public mobility, the use of trams and hybrid buses enables partial electrification. In contrast, private mobility remains dominated by renewable liquid fuels.

Reintegration of local storage

Removing the assumption of environmental neutrality for imports leads to a reorganization of the energy system, marked by a significant return of local storage technologies.

Total storage reaches nearly 48 TW h, representing a substantial increase compared to previous scenarios. This trend is illustrated in Figure 3.9, which compares the installed capacities of different storage technologies across the three scenarios under study.

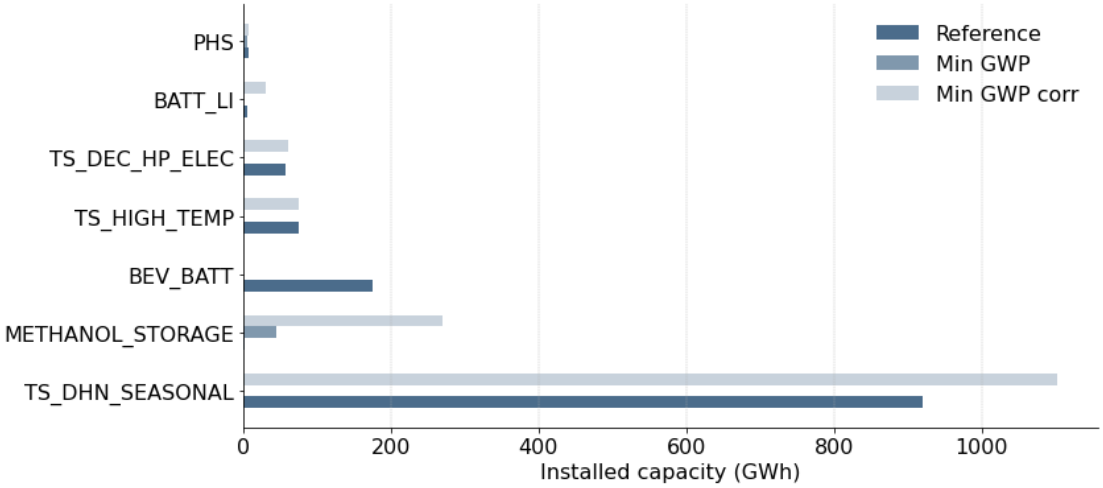


Figure 3.9: Installed storage capacities by technology in the three main scenarios: **Reference**, **Min gwp** and **Min gwp corrected** . Reintegrating the GWP_{op} of imported vectors leads to a significant return of local storage solutions, particularly seasonal thermal storage.

Thermal storage options, both at high and low temperatures, are once again mobilized. Li-ion batteries, which are absent in the **Min gwp** scenario, see their installed capacity multiplied by a factor of six due to increased electrification and a greater reliance on electricity storage.

The case of methanol is particularly illustrative. In the reference scenario, methanol is primarily allocated to non-energy uses. In the corrected scenario, it is also used for mobility, especially for freight transport, resulting in a significant increase in stored volumes. This shift stems from the partial relocalization of methanol production through domestic pathways such as methane conversion, biomass or electrochemical synthesis which become more advantageous than direct imports, now penalized by the GWP_{op}.

Storage thus becomes essential to absorb temporal mismatches between intermittent local production and consumption needs. The diagram in Figure 3.10 illustrates this complexity.

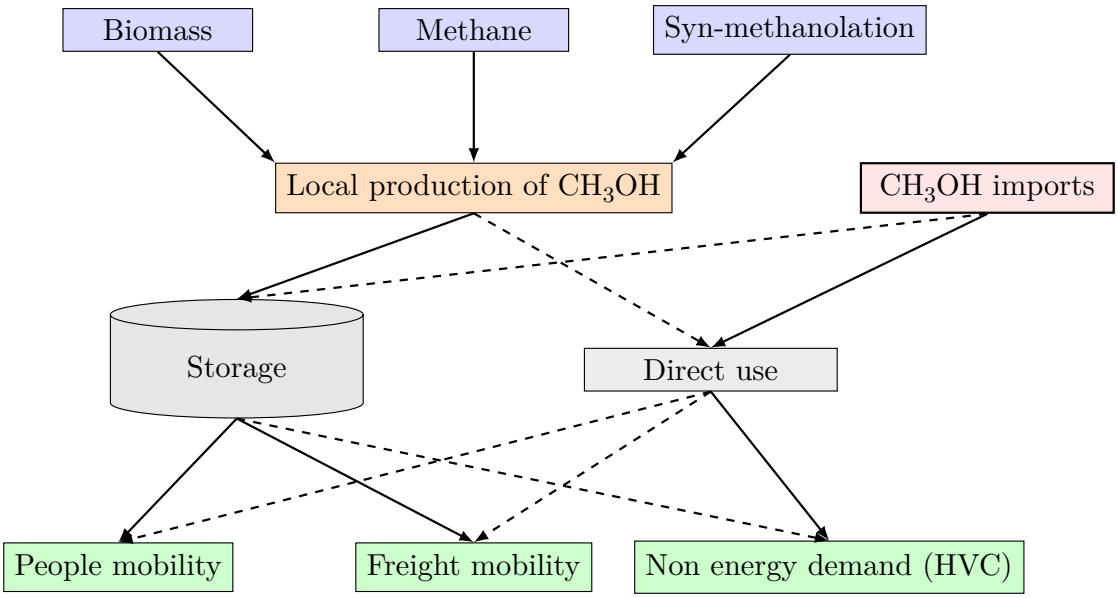


Figure 3.10: Structure of methanol flows in the **Min gwp corrected** scenario. Solid arrows indicate the main flows identified by the model, while dashed arrows represent a hypothetical distribution based on plausible techno-economic logic (such as the variability of local production or the flexibility of end-uses), which cannot be explicitly confirmed by the results.

At this stage, the model's granularity does not allow for a definitive attribution of the origin of stored methanol. However, it is plausible that locally produced methanol, potentially more intermittent, is primarily directed toward storage, while imported methanol, which is more stable, is used directly.

Reconfiguration of mobility

Mobility patterns adapt to the penalization of imported vectors. FCEV are replaced by gasoline cars powered by bioethanol. Buses running on biogas are substituted with biodiesel buses and Fuel Cell Electric Trucks (FCET) are replaced by trucks using biodiesel or hydiesel. This transition is explained by the fact that neither biodiesel nor bioethanol dominates the energy system at a global level and thus were not penalized. Their increasing role will be further examined in Section 3.6, dedicated to mobility.

Shift in resource usage

Figure 3.11 shows the evolution of the relative shares of the different resources across the scenarios. Natural gas and waste disappear entirely, likely due to their high carbon intensity. Hydrogen and ammonia, although only slightly penalized in terms of GWP, are also heavily marginalized, probably because of the high costs and significant GWP associated with hydrogen storage. Since ammonia is used as an intermediate vector for hydrogen production, its reduced use directly leads to a decline in its production. In contrast, methanol regains a significant role in the energy mix. Finally, certain local resources, such as wood and wet biomass, are once again mobilized.

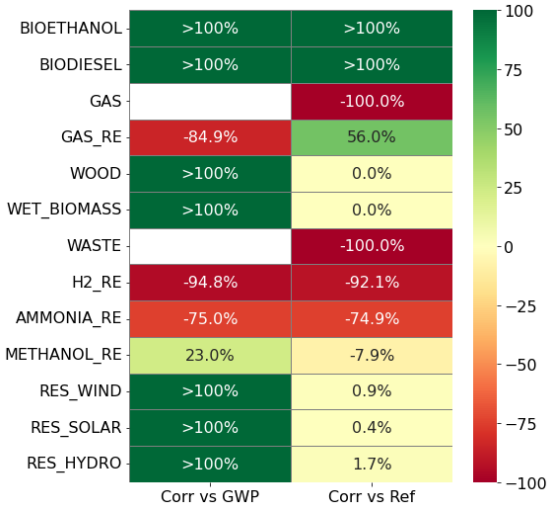


Figure 3.11: Relative change in resource availability in the **Min gwp corrected** scenario, compared to the **Min gwp** (Column 1) and **Reference** (Column 2) scenarios. Values indicate the percentage variation in annual resource availability in EnergyScope TD.

Thanks to these changes, imports account for 57 % of the energy mix, which is close to the reference scenario. This suggests that penalising GWP_{op} partially corrects the distortions of the **Min GWP** scenario.

These changes highlight a broader trend: when imports are associated with an environmental cost, the system relocates production and reintegrates local technologies. GWP_{op} thus becomes a strategic lever in technological decision-making.

3.3.4 Towards a more balanced system, still far from neutrality

The total GWP of the corrected scenario reaches approximately 18.85 Mt CO_2eq/y, compared to 10 Mt CO_2eq/y in the reference scenario. This increase is primarily driven by the inclusion of the GWP_{op} of imported energy carriers, which effectively triples the system's GWP_{op}. It highlights a key tension: lifting the neutrality assumption enables a more realistic rebalancing but is not sufficient to achieve climate neutrality. The result is higher than the values reported in Section 2.1, as this analysis does not account for the ETS mechanism and applies a conservative estimation of emissions from imported vectors. Nevertheless, when compared with the carbon budget proposed by Rixhon et al. [69], it falls within the acceptable range.

Conclusion

Integrating a realistic GWP_{op} for imported vectors restores more credible trade-offs in the energy system. It promotes the return of local storage, greater technological diversity and partial relocalization of flexibility options. This corrected scenario provides a robust foundation for analyzing the remaining uncertainties, particularly those linked to GWP_{constr}, which are addressed in the next section.

3.4 Stochastic analysis of storage technologies

This section investigates the extent to which uncertainty in the GWP_{constr} of storage technologies influences the outcomes of the modeled energy system. Using RHEIA, two levels of uncertainty ($\pm 20\,\%$ and $\pm 75\,\%$) were tested. The objective is twofold: to assess the overall robustness of the system to these variations and to identify critical parameters through a Sobol sensitivity analysis.

3.4.1 Effects of uncertainty on the GWP_{constr} of storage technologies

The probability distributions obtained for each uncertainty range are compared to evaluate the stability of average outcomes and the extent of variability introduced. These initial results provide insight into the system's overall sensitivity to assumptions about the GWP_{constr} of storage technologies.

Two analyses were conducted using RHEIA, varying only the GWP_{constr} values of storage technologies. In each case, central values are based on Table 2.1 presented

in Section 2.3. The first simulation considers an uncertainty of ±20 %, following the methodology proposed by Moret [54], which reflects a moderate level of uncertainty in the absence of precise data.

As illustrated in Figure 3.12, this moderate uncertainty results in a narrow distribution of the total GWP of the energy system. A second simulation, exploring a broader uncertainty of ±75 %, slightly widens the distribution without altering the mean value. These results suggest that, even under significantly amplified uncertainty, the overall impact on the system remains limited.

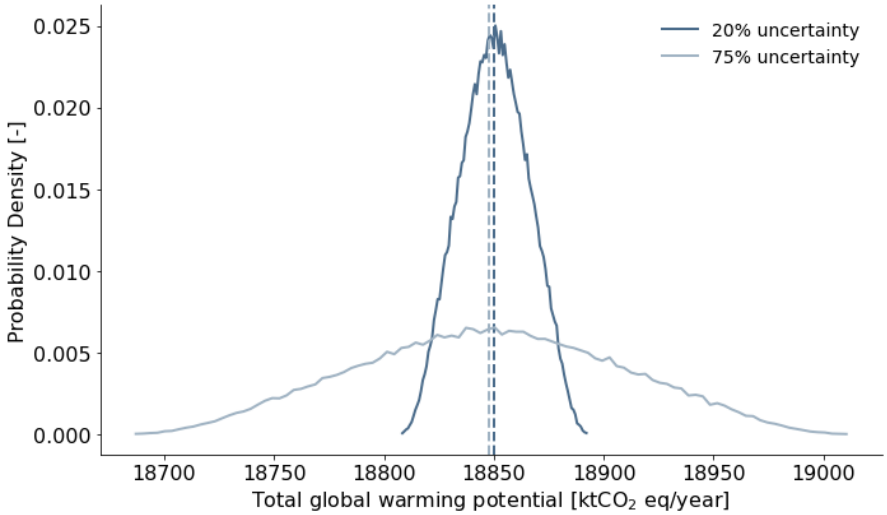


Figure 3.12: Probability density distribution of the total system GWP in kt CO_2eq/y for two uncertainty levels applied to the GWP_{constr} of storage technologies: ±20 % (dark line) and ±75 % (light line). Vertical dashed lines indicate the mean value of each distribution. The results show limited variability in the total GWP, even under high uncertainty levels.

The summary statistics in Table 3.5 confirm this observation. The standard deviation reflects the extent of dispersion: the higher it is, the more sensitive the system is to input uncertainties [14]. The LOO error is used to assess the quality of the surrogate model; its low value indicates the reliability of the obtained approximation [48].

	20 % **uncertainty**	75 %**uncertainty**
Mean [kt CO_2eq/y]	18 850	18 848
Standard deviation [kt CO_2eq/y]	15.4	59.1
Standard deviation [%]	0.08	0.3
LOO error [-]	$3.2 \cdot 10^{-5}$	$3 \cdot 10^{-3}$

Table 3.5: Statistical results of the stochastic simulations conducted on two uncertainty scenarios applied to the GWP_{constr} of storage technologies.

The means being nearly identical and the standard deviations relatively low, it can be concluded that the simulated energy system is robust with respect to these specific uncertainties.

This low sensitivity is explained by the uneven distribution of GWP_{constr} across technology categories. More than 88 % of construction emissions are attributed to production technologies, with photovoltaic systems being the dominant contributor. In contrast, storage technologies account for less than 1 % of total construction emissions. As a result, even large variations in their GWP_{constr} only have marginal effects on the overall system outcome.

In this context, a prospective update of the GWP_{constr} values for storage technologies by 2050 does not appear necessary, as their uncertainty has a negligible impact on the global results of the model.

3.4.2 Sensitivity analysis using Sobol indices

As seen earlier, the impact on total GWP remains limited. This could lead to the conclusion that these parameters are negligible for the overall planning of the energy transition. However, such a superficial reading masks finer sectoral dynamics. Variations in the GWP_{constr} can significantly influence the technological structure of the system. They affect trade-offs between local and imported resources, as well as between electric and thermal vectors. To highlight these more subtle effects, a sensitivity analysis was carried out using Sobol indices and cross-correlation matrices. This study focuses on a restricted but relevant subset of uncertain parameters.

Sobol indices

In this study, indices were computed for two representative levels of uncertainty: 20 % and 75 %. The aim is to identify which storage technologies' GWP_{constr} most influence the model outcomes.

The results, shown in Figure 3.13, indicate that high-temperature storage exhibits the highest Sobol indices, making it the main source of variability in total GWP. Decentralized storage using heat pumps ranks second. Seasonal storage, although widespread, appears to have little influence, with a maximum index of only 0.06.

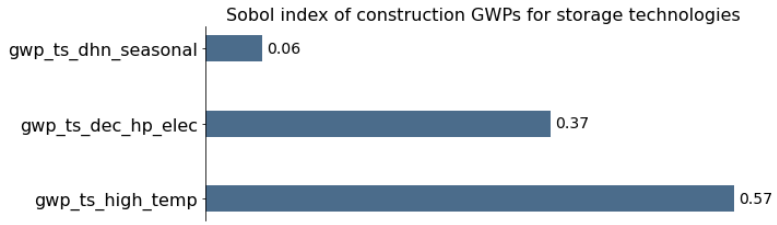


Figure 3.13: Significant Sobol indices associated with the GWP_{constr} of storage technologies. The values shown correspond to results obtained for two levels of uncertainty (±20 % and ±75 %). The indices are identical in both cases, with high-temperature storage technologies clearly dominating the sensitivity results.

To further interpret these results, an initial graphical analysis was conducted using boxplots of installed capacities. This step aimed to detect technologies exhibiting significant variability in response to uncertain GWP values. These technologies were then subjected to targeted analysis through cross-correlation matrices. All boxplots and correlation matrices are provided in Appendix C.

This stepwise approach enabled the identification of technologies that are truly sensitive to uncertainties in the GWP_{constr} of storage technologies, while excluding those whose behavior remains stable regardless of parameter variations.

Based on the Sobol indices and the observed correlations, only technologies that ranked among the top three most influential or showed a significant index were selected for detailed analysis.

Correlations between $\mathrm{GWP}_{\mathrm{constr}}$ uncertainties and sectoral responses

Figure 3.14 presents the correlations between a subset of the uncertain parameters, specifically the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies and the electrification rates of various end-use sectors. These correlations help identify which parameters significantly influence the technological orientation of final energy uses.

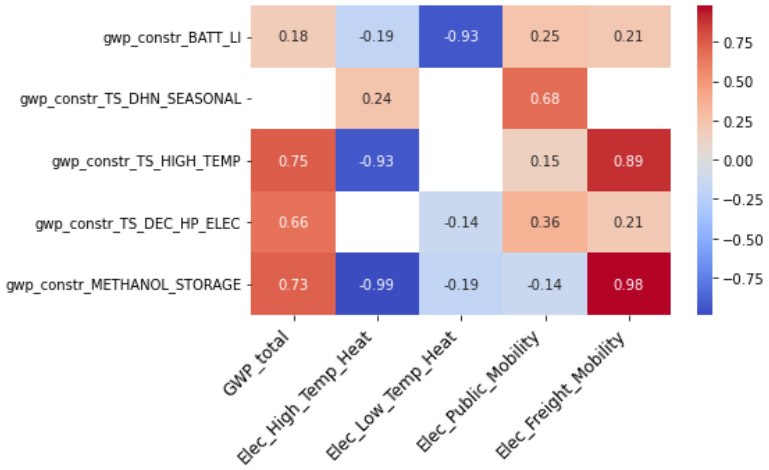


Figure 3.14: Correlations between the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies and sectoral electrification rates. This indicates that certain storage options may either support or hinder electrification depending on their environmental profile. Notably, the electrification of private mobility is not observed in any of the scenarios.

Several parameters show strong correlations with the system's total GWP, indicating a systemic influence on the results. However, the relationship between presence in the mix and actual influence is not straightforward. Seasonal storage, for instance, is highly present in the reference configuration but has only a limited impact on the key variables, an observation consistent with its low Sobol index. Conversely, methanol exhibits high correlations with numerous indicators, including total GWP, despite not being identified as influential in the Sobol analysis. This suggests that methanol plays an indirect yet central role in system trade-offs, particularly due to its flexibility of use.

To complement this cross-analysis, Figure 3.15 highlights the correlations between the same uncertain parameters and a selection of sectoral and technological indicators.

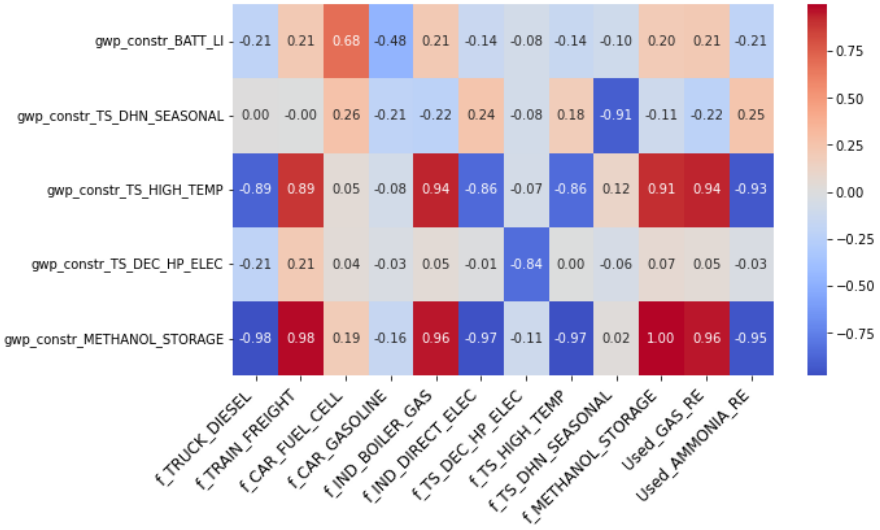


Figure 3.15: Correlations between the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies and the shares of key technologies as well as the use of certain resources.

The results show that lithium-ion battery storage is strongly correlated with a decrease in the electrification of low-temperature heat. This may be explained by its positive interactions with certain gas-dependent technologies. High-temperature thermal storage, in turn, influences not only its own usage sector but also freight mobility, revealing complex intersectoral trade-offs. Methanol-based storage shows significant influence on both high-temperature heat and freight transport. Combined with its high GWP and strong correlations with numerous other technologies, this confirms its strategic role in system-wide trade-offs. One can conclude that even a seemingly minor variation in an uncertain parameter may trigger a substantial shift in the optimized technology mix.

Correlations with energy resources also yield valuable insights. High-temperature and methanol-based storage are both strongly correlated with increased use of renewable gas, while showing a negative correlation with renewable ammonia. These trends highlight implicit substitutions between energy carriers, largely driven by the perceived environmental impact of storage technologies.

In the absence of reliable information on these parameters, the model may therefore underestimate or overestimate the degree of electrification, compromising the consistency of decarbonization pathways. These signals suggest that storage technologies, depending on their environmental profile, can either support or hinder electrification. They foreshadow future tipping points between heat pumps, gas boilers and reliance on imported vectors.

Conclusion

The correlation matrix analysis highlights the structuring role of thermal storage in shaping the technological orientation of the energy system. By directly influencing the installed capacity of several local technologies, storage conditions the extent of electrification, particularly in heat-related sectors. However, its influence is not limited to this domain: strong correlations with certain transport vectors, notably freight, reveal a systemic reach. Storage thus emerges as an intersectoral coupling factor whose sensitivity affects both heat and mobility.

The link between storage technologies and energy imports is equally revealing. The observed positive correlation between the GWP_{constr} of certain storage technologies and the use of imported vectors, particularly renewable gases, suggests a clear trade-off: when the environmental cost of local storage becomes too high, the model reallocates flexibility to external resources. This trend, already identified in global scenarios, is confirmed here more precisely through sensitivity analysis.

A key takeaway from this section is that, while the GWP_{constr} of storage technologies has little impact on the system's total GWP, its uncertainty can generate significant sectoral effects. This is particularly relevant for final-use electrification, energy autonomy and the choice between local and imported technologies. Even without an in-depth prospective analysis later in this thesis, it is essential to remain aware of the order of magnitude of these impacts. It is not so much the exact parameter value that matters, but the importance of including it within a robustness logic: having a rough estimate of its effect helps maintain coherence with consistent transition trajectories.

The correlations identified in this section directly feed into the analyses that follow. They highlight the existence of changeover dynamics, ie thresholds beyond which a technology becomes dominant or disappears from the optimised system. These tipping points may arise across different levels: in imports, depending on the relative environmental competitiveness of synthetic carriers; in storage technologies, with some becoming locally dominant while others are excluded; and in mobility patterns, with transitions between electric and thermal drivetrains.

These tipping points will be explored in detail in the following sections. They will help clarify the technological trade-off mechanisms at work in the model, as well as their sensitivity to uncertain parameters.

This cross-cutting analysis confirms that storage technologies are not merely secondary system adjustments. Their perceived environmental compatibility,

whether overestimated or underestimated, can be enough to shift the energy system from one technological regime to another, with cascading effects on electrification, import flows and mobility strategies.

3.5 Tipping point analysis and phase-out thresholds of storage technologies

This section examines critical competitiveness thresholds in response to directed variations in the GWP_{constr} of storage technologies. Beyond their direct effects on installed storage capacity, these perturbations also influence the structure of other sectors within the energy system. The analysis thus reveals tipping dynamics, mechanisms of technological interdependence and systemic reallocations. The indirect role of the GWP_{op} of imported vectors is also explored to better understand the interplay between local storage and dependence on external resources.

3.5.1 Additional assumption on non-dominant vectors

The scenario used in this analysis differs from the one presented earlier in the chapter. It was specifically designed to test the system's sensitivity to environmental parameters using a two-step approach.

In the first step, GWP_{op} values were assigned to imported renewable energy vectors, in line with the methodology described in Section 2.3.4. This step corrects the optimization bias in favor of imports by internalizing the associated environmental externalities. It leads to the **Min gwp corrected** scenario, in which the share of local resources is significantly increased.

However, some resources, such as bioethanol and biodiesel, are imported, were never identified as dominant at the scale of the overall energy system. As such, they were not penalized in the initial analysis of dominant vectors. Yet, these biofuels do occasionally appear as dominant within the private mobility sector, which suggests a potential competitive advantage if their GWP_{op} is assumed to be zero.

To ensure methodological consistency with the treatment of other vectors, an additional assumption was therefore introduced: bioethanol and biodiesel vectors were also penalized by assigning them a GWP_{op}, even though they never dominated the global system. This approach aims to prevent them from retaining an artificial residual advantage in certain marginal configurations.

To determine a relevant value, several simulations were conducted by progressively increasing the GWP_{op} of these resources up to the same upper bound already used for other imports, i.e., 0.09 kg CO_2eq/kWh.

Figure 3.16 shows that private mobility technologies dependent on these fuels completely disappear from the energy mix beyond 0.06 kg CO_2eq/kWh, marking the tipping point from biodiesel- and bioethanol-based vehicles toward hydrogen-based alternatives. Although this value is not derived from a full adjustment process as was done for dominant vectors, it remains lower than the GWP_{op} values assigned to other imports.

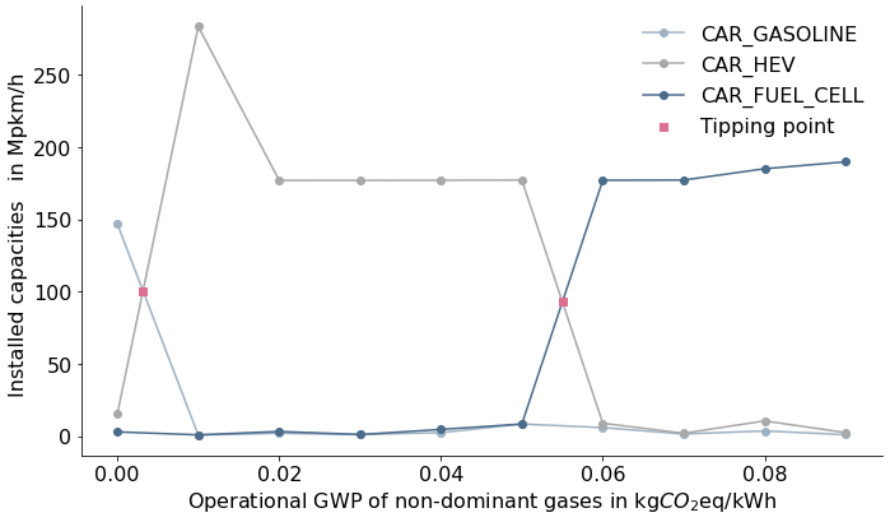


Figure 3.16: Evolution of installed capacities in private mobility as a function of the GWP_{op} assigned to non-dominant vectors. The tipping point is observed at 0.06 kg CO_2eq/kWh, beyond which technologies relying on these fuels cease to be competitive. The figure highlights the inversion of technological dynamics within the private mobility sector, with a clear shift toward fuel cell vehicles. It should be noted that the GWP_{op} values of the dominant gases are those reported in Table 3.4.

This slightly conservative choice ensures overall consistency in the environmental treatment of imported vectors, while correcting the initial favorable bias granted to biofuels.

All simulations related to threshold and tipping point analyses were therefore conducted using a value of 0.06 kg CO_2eq/kWh for non-dominant vectors. The limitations and implications of this choice will be discussed in more detail later in this section.

This assumption significantly alters technological equilibria, particularly in the private mobility sector, where the comparative advantage of vehicles using these fuels is reduced. It enables the identification of new tipping points and allows for a more refined assessment of robust transition strategies in response to the reassessment of the environmental impacts of these renewable liquid fuels.

3.5.2 Systemic reduction of storage under environmental pressure

When the GWP_{constr} of storage technologies becomes high, the modeled system exhibits a specific response: instead of substituting one storage technology with another, it reduces the overall level of storage. In these cases, the assigned values are particularly high, with none below twice their current levels and the technologies whose GWP is increased are those used in most scenarios. While such situations represent extreme cases, the purpose here is to observe the underlying trend.

This behavior stems from the nature of storage itself, which does not serve a final energy use, but rather functions as a vector of systemic flexibility. Therefore, when the environmental trade-off becomes unfavorable, the model may choose to partially or entirely do without it, without directly compromising the satisfaction of final energy demands.

As illustrated in Figure 3.17, beyond a certain GWP threshold, both installed capacity and annual storage flows drop sharply. This shift indicates a systemic reconfiguration of the energy mix: rather than maintaining an infrastructure that has become too costly in terms of embodied emissions, the model reallocates resources to more climate-efficient solutions.

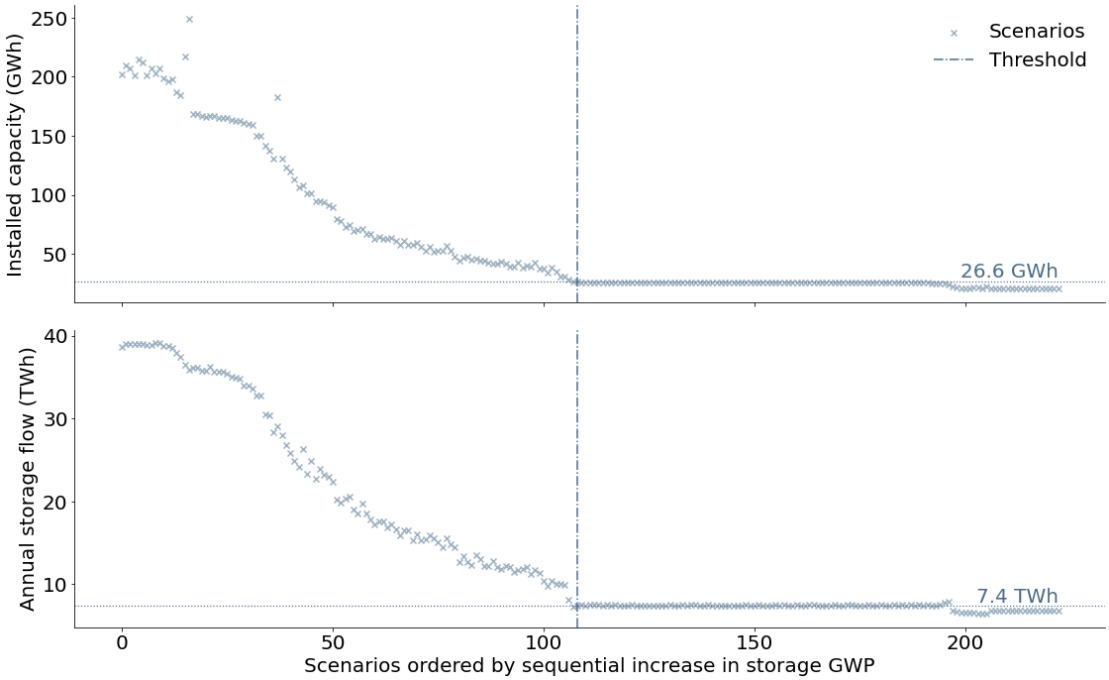


Figure 3.17: Evolution of installed capacity and storage usage as a function of $\mathrm{GWP}_{\mathrm{constr}}$. Each point corresponds to a scenario where the dominant storage technology sees its $\mathrm{GWP}_{\mathrm{constr}}$ increase until it loses dominance, triggering the entry of another technology. Beyond a certain threshold, storage is drastically reduced or even removed from the optimized energy mix.

The objective of this analysis is not to define a universal critical threshold beyond which storage becomes unviable, but rather to highlight the decision-making logic of the model. The GWP values associated with the drop in storage are significantly higher than the estimates available in the literature. Nevertheless, they reveal an interesting dynamic: in the face of high environmental cost, no alternative storage technology takes over. The system therefore massively shifts away from this function.

This reduction continues until it reaches a floor level, where only storage forms deemed essential by the model are retained. Among these, Pumped Hydro Storage (PHS) maintains a minimal presence of 5 GW h, representing about one fifth of the remaining total capacity. This behavior underlines the low resilience of storage, as a technology category, when subject to environmental pressure specifically targeting its construction phase.

3.5.3 Frequency of presence of storage technologies

The analysis of the frequency with which storage technologies appear in the simulated scenarios helps identify the solutions most systematically selected by the model. This relative occurrence, presented in Figure 3.18, serves as an indicator of robustness or, conversely, marginality.

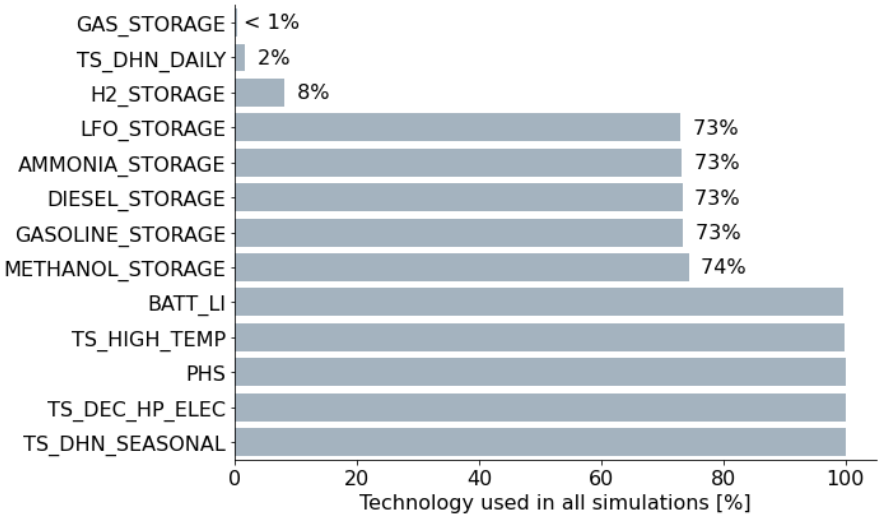


Figure 3.18: Share of scenarios in which each storage technology appears in the optimized system. Technologies with very low occurrence are considered structurally non-competitive within the explored design space.

Some technologies appear in more than 70 % of the scenarios, indicating strong systemic robustness. This is notably the case for high-temperature thermal storage, centralized seasonal storage, PHS and synthetic fuels such as methanol.

Conversely, other technologies, such as gas storage, daily thermal storage or hydrogen storage, exhibit very low occurrence rates, below 10 %. Their marginal presence suggests limited competitiveness in most of the simulated scenarios.

Storage technologies not shown in this figure are those with an appearance frequency below a minimal threshold of representativity. They are considered structurally non-competitive and will not be analyzed further in the remainder of the section.

3.5.4 Influence of the $\mathrm{GWP}_{\mathrm{op}}$ of imports on storage

The progressive introduction of $\mathrm{GWP}_{\mathrm{op}}$ for imported renewable energy carriers significantly influences the composition of the optimal storage mix. This section

aims to analyze, using the dominance-based approach described in Section 2.3.4, how the increase in these values affects the appearance, disappearance, or reorganization of different storage technologies.

When all GWP_{op} values for imported carriers are still set to zero, only two storage technologies appear: methanol-based storage and PHS, the latter being constrained to its minimum capacity of 5 GW h. As soon as the GWP_{op} of renewable gas, the dominant resource, is increased to 0.01, the system begins to reactivate various storage options. In particular, seasonal storage immediately reappears and rapidly exceeds a significant installed capacity.

Table 3.6 presents the main critical thresholds observed, depending on the imported energy carrier whose GWP_{op} is modified. All data in this table are extracted from the simulation `.csv` files, available in Appendix F.

Technologies		**GAS**	**H_2**	**CH_3OH**	**NH_3**	**ND**
Cent. seasonal	ET	0.01	0	0	0	0
	RTP	0.03	0.02	0	0.02	0
Li-ion battery	ET	0.09	0.08	0.11	0.06	0
	RTP	0.1	0.09	0.11	0.06	0.06
PHS	RTP	0.07	0.06	0	0.04	0
Dec. electrical HP	ET	0.01	0	0	0.01	0
thermal Sto. industries	ET	0.07	0.06	0	0.05	0
H_2 storage	ET	0.07	0.06	0	0.05	0
	POT	0.08	0.07	0	0.05	0
Diesel storage	ET	0.08	0.07	0.06	0.05	0
Gasoline storage	ET	0.08	0.07	0.06	0.05	0
LFO storage	ET	0.08	0.07	0.06	0.05	0
NH_3 storage	ET	0.01	0	0	0	0.01
CH_3OH storage	ET	0.08	0.07	0.07	0.05	0
	RTP	0.08	0.08	0.11	0.05	0
	TP	0.09	0.09	0.11	0.06	0

Table 3.6: Critical thresholds for storage technologies in response to increasing GWP_{op} of imported energy carriers. All values represent GWP_{op} levels expressed in kg CO_2eq/kWh. Emergence Threshold (ET), Tipping Point (TP), Reverse Tipping Point (RTP), Phase-Out Threshold (POT) and ND = non-dominant vectors such as biodiesel and bioethanol.

Several technologies do not appear in any scenario, regardless of the values assigned to the GWP_{op}. This is the case for most decentralized thermal storage technologies, BEV and PHEV batteries, daily storage systems and gas storage.

Conversely, some technologies appear very early and become anchored in the system. This includes seasonal storage, PHS, electric HP and industrial thermal storage. These stable technologies show no variation when only the GWP_{op} of biodiesel and bioethanol are modified.

It is important to note that the reverse tipping point for PHS does not indicate a dominance shift, but rather the attainment of its maximum allowed capacity in the model, set at 6.5 GW h. This means that the system fully mobilizes the potential of this technology as soon as the GWP_{op} reaches moderate thresholds.

Hydrogen storage, although very marginal, is one of the few storage technologies to disappear entirely as a result of increasing GWP_{op}. This disappearance occurs when the GWP values of renewable gas and hydrogen are already high, indicating a rapid loss of competitiveness for this technology compared to other available storage options.

Diesel, gasoline, LFO and ammonia storage options remain present despite increases in GWP, suggesting that under certain configurations, local storage remains preferable to further imports.

Figure 3.19 highlights the specific dynamics between three storage technologies: methanol storage, ammonia storage and centralized seasonal storage.

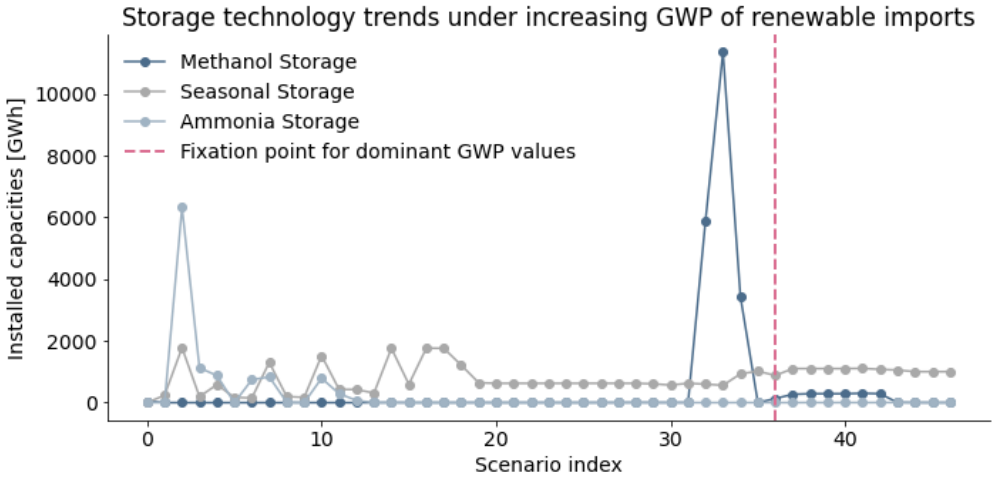


Figure 3.19: Evolution of installed capacities for seasonal, methanol and ammonia storage as the GWP_{op} of imports increases. Seasonal storage reappears once gas reaches 0.01, quickly gaining importance. Ammonia shows early fluctuations, while methanol briefly dominates, stabilises around 280 GW h, then declines when biodiesel and bioethanol acquire a non-zero GWP_{op}.

Seasonal storage becomes dominant from the very first increases in GWP_{op}, but experiences strong initial fluctuations, often in direct opposition to ammonia storage. The latter shows very unstable behavior during the early iterations, with occasional peaks in capacity, before its variations gradually stabilize as the GWP continues to rise.

The emergence of methanol storage appears to be independent of the initial increases and occurs more sporadically. It briefly becomes dominant in certain configurations before declining again. It temporarily stabilizes around 280 GWh when only the GWP values of biodiesel and bioethanol are modified, then drops again when these reach a threshold of 0.06.

This analysis confirms that increasing the GWP_{op} of imported carriers leads to significant reconfigurations of the storage mix. Seasonal storage quickly emerges as a robust alternative, while methanol and ammonia exhibit more transient and unstable dynamics. These results highlight the structuring role of a few resilient technologies under stronger environmental constraints.

3.5.5 Critical thresholds and identified transitions

This subsection presents two types of results related to the effects of the GWP_{constr} of storage technologies: on the one hand, the specific thresholds associated with each technology (emergence, loss of dominance, disappearance) and on the other hand, the observed shifts between technologies in response to variations in a triggering GWP.

Critical thresholds by technology

Table 3.7 presents the main critical thresholds identified for storage technologies in relation to their GWP_{constr}. These thresholds are derived from parametric simulations, whose corresponding graphs are shown in Appendix D and are expressed in kg CO_2eq/kWh of installed capacity. They enable the characterisation of different transition regimes such as those described in Section 2.4.2.

Technologies	ET	RTP	TP	POT	CV
Li-ion Batteries	X	X	113 (+85 %)	122 (+99 %)	61.3
Pumped hydro storage	X	X	X	98 (+1 000 %)	8.33
Dec. electrical HP	X	0	27 (+380 %)	69 (+1 129 %)	5.62
Cent. daily	1.2 (-97 %)	0	X	X	37.2
Cent. seasonal	X	X	4.84 (+448 %)	4.84	0.884
Thermal Sto. industries	X	0	25 (+324 %)	91 (+1 400 %)	5.89
Gas storage	0.72 (-87 %)	0.72	X	X	5.72

Table 3.7: Environmental tipping thresholds for storage technologies expressed in kg CO_2eq/kWh of installed capacity. Emergence Threshold (ET), Reverse Tipping Point (RTP), Tipping Point (TP), Phase-Out Threshold (POT) and CV = Current Value of GWP_{constr}. Values in parentheses indicate the relative deviation from the current value.

Some technologies demonstrate strong resilience. Centralized seasonal storage, for instance, remains present across all tested scenarios and only disappears at very high GWP levels well beyond reference values found in the literature. This indicates a structurally high level of competitiveness.

Conversely, other solutions only appear in the optimized mix when their GWP is reduced to zero and even then never reach a significant share. This is the case for several decentralized storage technologies or options based on liquid fuels. Their absence suggests intrinsic non-competitiveness that cannot be offset by isolated environmental improvements.

The crosses indicated in the table denote the absence of an identifiable threshold, which may result from different situations:

- systematic presence in the case of emergence thresholds;
- constant dominance for reverse tipping points;
- total absence of dominance for tipping points;
- or persistence across all scenarios despite progressive degradation of the GWP, in the case of phase-out thresholds.

Some specific behaviors deserve clarification. For PHS, the value indicated for the phase-out threshold corresponds to the point at which the technology reaches its

minimum capacity allowed in the model, without fully disappearing.

For the decentralized electric heat pump, the tipping point does not signal a loss of dominance, but rather the onset of a gradual decline in installed capacity. This decline intensifies until reaching a stabilization threshold beginning at 69 kg CO_2eq/kWh.

In the case of high-temperature storage for industrial use, the identified tipping point marks the beginning of a decline after the capacity had previously remained stable. It therefore represents a turning point in trajectory rather than a shift in dominance.

Finally, for some less frequent technologies, such as daily thermal storage or gas storage, an emergence threshold was identified. This suggests that their marginality is indeed linked to their initial GWP.

Tipping points between storage technologies

Based on the figures presented in Appendix D.1, several tipping points between storage technologies have been identified. These correspond to situations where the variation in the GWP_{constr} of a given technology significantly affects the trajectory of one or more others, revealing compensation or substitution relationships within the optimized system. Table 3.8 summarizes the main interactions observed.

Trigger technology	Affected technology	Effect
Li-ion battery	Cent. seasonal Thermal Sto. industries Dec. electrical HP Methanol Sto.	Direct compensation ↘ if $GWP_{constr} \leq 6$ kg CO_2eq/kWh ↘ if $GWP_{constr} \leq 41$ kg CO_2eq/kWh ↗ if $GWP_{constr} \geq 110$ kg CO_2eq/kWh
PHS	Li-ion battery	Partial substitution if $GWP_{constr} \geq 98.7$ kg CO_2eq/kWh
Thermal Sto. industries	Methanol Sto.	↗ followed by stabilisation when $GWP_{constr} \geq 88$ kg CO_2eq/kWh

Table 3.8: Cross-technology tipping effects observed in the storage sector. Arrows indicate the direction of capacity change; threshold values refer to the GWP_{constr} of the trigger technology.

Li-ion batteries appear as a central lever in these cross-technology dynamics. Variations in their GWP_{constr} lead to significant effects on several other technologies. As shown in Figure 3.20, a direct compensation by seasonal storage is observed as soon as the battery GWP changes. Similarly, a substantial reduction in

the installed capacity of high-temperature thermal storage and decentralized heat pumps is observed when the battery GWP falls below certain thresholds. Conversely, an increase in methanol storage occurs when the battery GWP exceeds 110 kg CO_2eq/kWh.

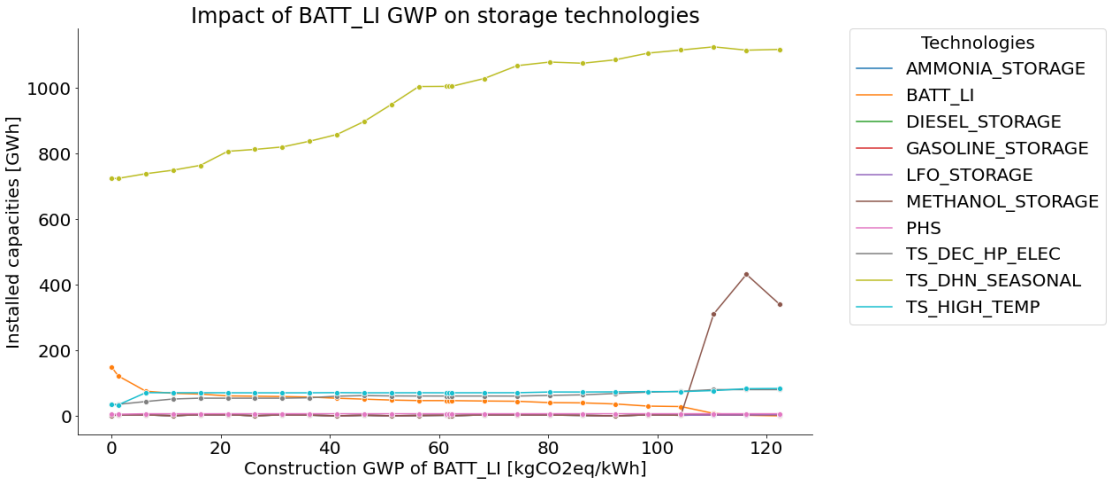


Figure 3.20: Evolution of installed storage technology capacities in 2050 as a function of the GWP_{constr} of lithium-ion batteries in kg CO_2eq/kWh. Other storage technologies are indirectly affected through mix reallocations, highlighting competitive interactions between storage solutions.

Other notable interactions have also been identified. When the installed capacity of PHS reaches its minimum in the optimized mix, partial substitution by Li-ion batteries is observed. Finally, an increase in the GWP of industrial thermal storage leads to a gradual rise in methanol storage capacity, which stabilizes at a relatively high level beyond 88 kg CO_2eq/kWh.

These results remain partial: only a few clear tipping points could be extracted, which can be explained by the complexity of the system and the intrinsic limitations of the visual approach adopted here. Not all cross-technology interactions can be inferred from graphical trends alone, especially when the technologies involved are only marginally represented in the mix or weakly sensitive to variations in GWP.

3.5.6 Validation of dynamics through systematic co-variations

The technological transitions previously identified from individual curves are here compared with the co-variations observed across all parametric simulations. These co-variations reveal interdependencies between technologies: modifying the GWP_{constr} of a given storage technology can systematically affect the installed capacity of other technologies. Such interactions reflect substitution mechanisms, complementarities, or partial independence within the energy system.

Table 3.9 summarizes the most significant relationships identified: for each triggering technology, the columns list other technologies whose installed capacity increased, decreased, or remained stable in more than 65 % of cases. Only systematic co-variations are reported here; the complete results are provided in Appendix D.

The percentages used should not be interpreted as statistical probabilities derived from random sampling. They represent frequencies observed in a controlled unidirectional variation of the GWP and should therefore be understood as indicators of systemic sensitivity rather than probabilistic robustness.

Technologies	Positive influence	Negative influence	Stable
Cent. seasonal	LFO Sto. Gasoline Sto. Diesel Sto. Ammonia Sto.		Cent. daily PHS PHEV battery BEV battery Gas Sto. Hydrogen Sto.
Dec. electrical HP		Li-ion Battery	Cent. daily PHS PHEV battery BEV battery Gas Sto.
PHS	Cent. seasonal Dec. electrical HP	Li-ion Battery	Cent. daily PHEV battery BEV battery Hydrogen Sto.
Li-ion Batteries		Cent. seasonal	Cent. daily PHS PHEV battery BEV battery Gas Sto. Hydrogen Sto.
Thermal Sto. industries		Methanol Sto.	Cent. daily PHS PHEV battery BEV battery Gas Sto.
Methanol Sto.	LFO Sto. Gasoline Sto. Diesel Sto. Ammonia Sto.		Cent. daily PHS PHEV battery BEV battery Gas Sto. Hydrogen Sto.
Hydrogen Sto.	Cent. seasonal Methanol Sto. LFO Sto. Gasoline Sto. Diesel Sto. Ammonia Sto.	Li-ion Battery	Cent. daily PHS PHEV battery BEV battery Gas Sto.

Table 3.9: Summary of systematic co-variations observed between storage technologies. Each cell indicates the technologies whose installed capacity increased, decreased, or remained stable in more than 65 % of simulations, in response to a variation in the GWP_{constr} of a triggering technology.

First, some technologies appear stable not because of actual systemic robustness, but because they are either absent or very weakly represented in most of the simulated scenarios. When comparing these results with the technological presence data (Figure 3.18), it becomes clear that daily thermal storage, BEV and PHEV batteries, as well as gas storage, are underrepresented with appearance frequencies below 10 %. Their apparent stability therefore stems more from a lack of influence than from a true capacity to withstand environmental variations. In contrast, the observed stability of PHS is confirmed by its strong representativity across scenarios, reflecting genuine robustness against environmental stress.

The case of high-temperature storage illustrates a pattern of targeted substitution. When it becomes less competitive, there is a systematic increase in the installed capacity of methanol storage. This reflects a partial compensation for the loss of thermal flexibility through a vector that is easier to store and deploy, suggesting a backup role in environmentally constrained trajectories.

A complementary cascading analysis revealed that two technologies, methanol and hydrogen storage, tend to appear under specific configurations. Methanol emerges consistently when key pillars of the system, such as seasonal or thermal storage, become too emissive to remain optimal. Hydrogen, by contrast, appears in a more transitional manner, temporarily serving as a buffer during phases of technological readjustment, as illustrated in the figures of Appendix D.

This second analysis makes it possible to compare the previously identified tipping points with a more systematic evaluation based on the frequency of co-variations. It thus provides a complementary framework for confirming, refining, or challenging the dynamics observed in Table 3.8 and the corresponding graphs.

The inverse relationship between Li-ion batteries and seasonal storage is fully confirmed: an opposite co-variation is observed in 78 % of scenarios, supporting the existence of a robust substitution mechanism between these two technologies. In contrast, the visually identified link between batteries and decentralized heat pumps appears less convincing: only 50 % of simulations show an opposing variation, suggesting a more marginal or conditional influence.

The substitution dynamic between PHS and Li-ion batteries is clearly validated, with an opposite variation systematically observed in 89 % of cases, consistent with the tipping point observed when PHS reaches its minimum capacity.

Finally, the dynamics involving methanol storage are also confirmed. An opposite variation relative to high-temperature thermal storage is observed in 76 % of scenarios and in 63 % of cases relative to Li-ion batteries. These results support the hypothesis of a compensatory mechanism for methanol storage, particularly in situations where dominant technologies become too emission-intensive to remain competitive. Contrary to what some limited graphical observations may have suggested, no unexpected dynamic emerges here; on the contrary, the statistical trends reinforce the robustness of the previous interpretations.

3.5.7 Indirect effects of storage on other technologies

This section examines the systemic impacts induced by variations in the GWP_{constr} of storage technologies on the installed capacities in other end-use sectors of the energy system.

Private mobility

In the case of private mobility, the results presented in previous chapters highlighted complex substitution dynamics between fuel cell, hybrid and electric vehicles. However, since the introduction of GWP_{op} for imported renewable resources, these dynamics have become fixed: FCEV remains systematically dominant, regardless of the variations applied to the GWP_{constr} of storage technologies.

This behavior suggests that the previously observed variations in the mobility sector were not directly caused by the storage technologies themselves, but rather by a global imbalance temporarily introduced by the GWP_{constr} values applied in the early scenarios. Moreover, even when a zero GWP is assigned to BEV battery or PHEV battery technologies, the associated vehicles experience a strong increase in installed capacity, but only for storage functions. They are therefore not used to provide mobility, but rather as backup vectors exploiting their battery capacity as a flexibility solution. This illustrates a partial decoupling between the technological function (mobility) and the actual role in the energy mix (stationary storage).

Freight transport sector

Special attention is given to the freight sector, which exhibits a distinct behavior. Indeed, FCET stands out as the only technology in this sector to experience such pronounced and systematic variations across all simulations involving the GWP_{constr} of storage technologies.

For example, in the case of Li-ion battery technology, Figure 3.21 shows that the installed capacity of FCET reaches a maximum precisely at the reference point of the GWP_{constr}, positioning it as the second-highest technology in the freight mix. However, as soon as the GWP_{constr} increases or decreases, its capacity drops sharply. This phenomenon is also observed in simulations involving other storage technologies, suggesting a structural instability specific to this technology.

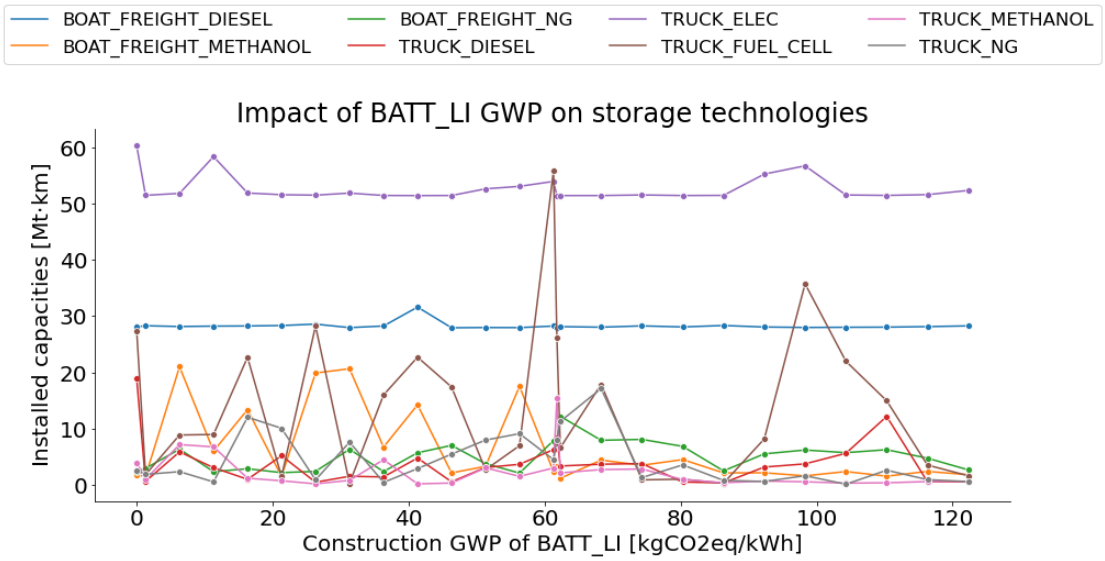


Figure 3.21: Evolution of installed freight technology capacities as a function of the GWP_{constr} of lithium-ion batterie. While most technologies remain relatively stable, noticeable variations are observed for FCET.

In contrast, technologies such as electric trucks or diesel-powered freight boats exhibit very high stability, regardless of the storage GWP being analyzed. This reinforces the hypothesis that FCET acts as a "buffer" technology activated occasionally by the optimizer to restore techno-environmental balance under constrained configurations.

Other sectors do not exhibit such pronounced behaviors. The full results from all simulations combining storage technologies and final-use sectors are available in Appendix F.

3.6 Tipping point analysis and phase-out thresholds for private mobility technologies

3.6.1 General substitution dynamics in the private mobility sector

Thanks to the numerous runs conducted using the dominance-based approach, an overall dynamic of the private mobility sector has been identified. This is illustrated in Figure 3.22. The system is initially dominated by fuel cell vehicles.

This dominance persists until the GWP_{constr} of hydrogen vehicles reaches approximately 50 kt CO_2eq/Mpkm/h. At this threshold, hybrid vehicles begin to appear in the mix, initiating a phase of alternation between the two technologies. This transition period extends up to GWP values of 70 kt CO_2eq/Mpkm/h for fuel cell vehicles and 20 kt CO_2eq/Mpkm/h for hybrids.

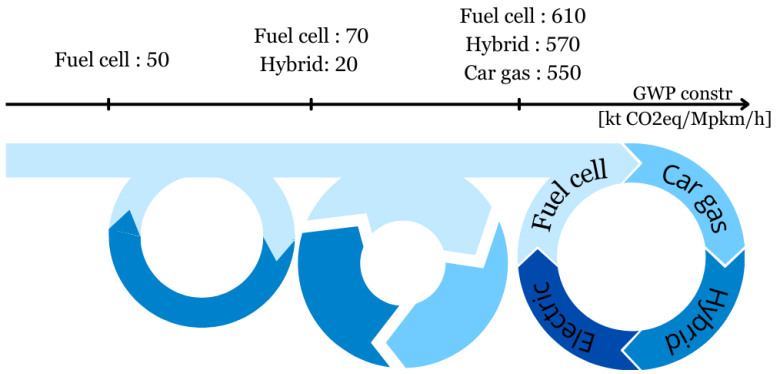


Figure 3.22: Succession of dominant private mobility technologies with increasing vehicle GWP_{constr} (kt CO_2eq/Mpkm/h). The figure shows the emergence of hybrid, thermal and electric options, along with transitions between technology families, revealing a cyclical dominance pattern.

Beyond these thresholds, internal combustion engine vehicles also become dominant. A new sequence then emerges, characterized by a regular alternation between fuel cell vehicles, thermal vehicles and hybrids. This dynamic remains stable over a wide range of GWP values.

Finally, when GWP_{constr} values reach high levels, a transition toward the dominance of electric vehicles occurs. This configuration appears to be durably stabilized: no reversal in trend was observed in the simulations conducted beyond these thresholds.

3.6.2 Influence of the GWP_{op} of imports on private mobility

A strong dependence of private mobility technologies on the GWP_{op} has been observed across all simulations. This sensitivity is explained by the fact that these technologies differ primarily by the energy carrier they use, making their environmental performance directly linked to the GWP associated with that carrier. The analysis developed in this section builds on the dominance-based approach presented in Section 2.3.4 and aims to identify the effects of a progressive increase in GWP_{op} values on the emergence, disappearance, or reorganization of the main mobility technologies.

Table 3.10 summarizes the critical thresholds identified for each technology. The data are derived from the parametric simulations and are available in `.csv` format in Appendix F.

Technologies		**H_2**	**CH_3OH**	**GAS**	**NH_3**	**ND**
Car fuel cell	TP	0.01	0	0.01	0.01	0
	RTP	0.09	0.11	0.1	0.06	0.06
Car HEV	ET	0.01	0	0.01	0.01	0
	RTP	0.09	0.11	0.1	0.06	0.01
	TP	0.09	0.11	0.1	0.06	0.06
Car methanol	ET	0.01	0	0	0.01	0
	TP	0.07	0.01	0.08	0.05	0
Car diesel	ET	0.01	0	0.01	0.01	0
Car NG	ET	0.01	0	0.01	0.01	0
Car gasoline	ET	0.01	0	0.01	0.01	0
	RTP	0.01	0	0.01	0.01	0
	TP	0.09	0.11	0.1	0.06	0.01

Table 3.10: Emergence Threshold (ET), Tipping Point (TP) and Reverse Tipping Point (RTP) for private mobility technologies as a function of the GWP_{op} of renewable imported vectors: hydrogen, methanol, gas, ammonia and non-dominant vectors (ND) such as biodiesel and bioethanol. Values are expressed in kg CO_2eq/kWh.

BEV and PHEV do not appear in any scenario, reflecting their lack of competitiveness under the tested configurations. However, some technologies, while not dominant, still show a non-negligible contribution. This is particularly the case for methanol-powered vehicles, which, between their emergence threshold and their own tipping point, supply on average one-third of the total mobility demand. This tipping point corresponds precisely to the moment when the technology becomes

marginal: its contribution drops sharply and never exceeds any significant threshold afterward.

These dynamics are illustrated in Figure 3.23, which shows the evolution of the main private mobility technologies in response to the progressive increase in the GWP_{op} of imported energy carriers.

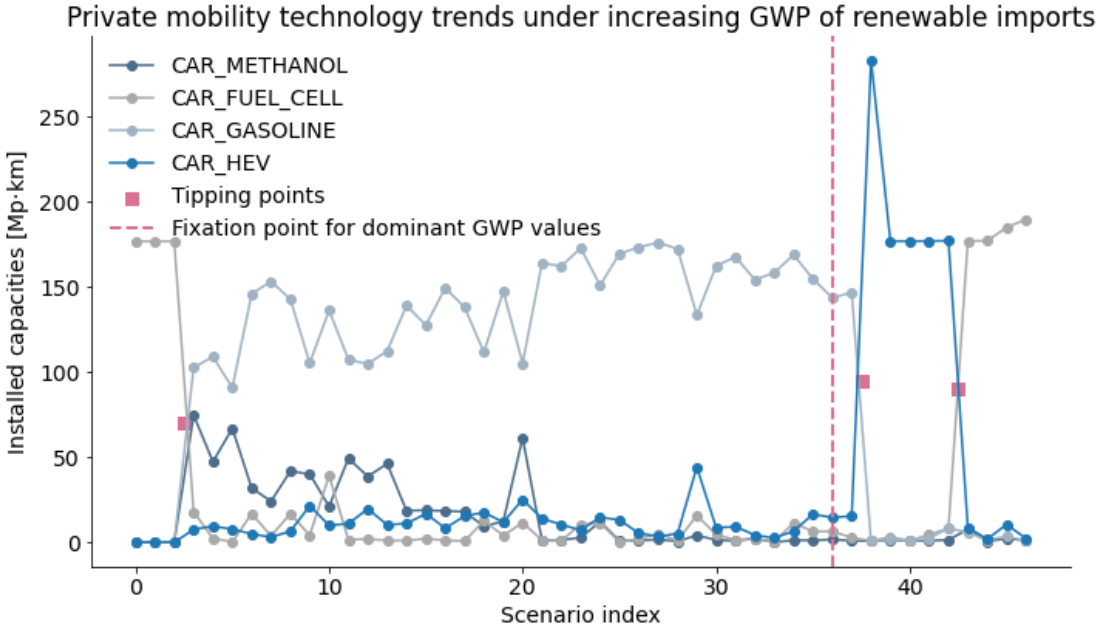


Figure 3.23: Evolution of installed capacities of major private mobility technologies under increasing GWP_{op} of renewable imports. Pink markers indicate changes in technological dominance. The dashed line corresponds to the GWP_{op} values used in the main scenarios.

As long as no GWP_{op} is accounted for in the model, FCEV overwhelmingly dominate the private mobility sector. However, the introduction of a non-zero GWP_{op} value for imported energy carriers is sufficient to shift dominance in favor of gasoline cars. The latter retain their dominant position until the GWP_{op} of the main carriers reaches their final values, namely: 0.09 kg CO_2eq/kWh for hydrogen, 0.10 kg CO_2eq/kWh for gas, 0.11 kg CO_2eq/kWh for methanol and 0.06 kg CO_2eq/kWh for ammonia. The ability of car gasoline to maintain dominance up to these levels indicates a certain robustness to environmental constraints applied to the main energy vectors.

In contrast, when the GWP_{op} of the non-dominant vectors is also increased, the system shifts toward dominance by HEV. This transition phase stabilizes over a relatively wide interval before FCEV regain dominance once the GWP_{op} of non-dominant vectors reaches approximately 0.06 kg CO_2eq/kWh.

Thanks to the position of the pink markers on the graph, it is possible to identify, for any given GWP_{op} value, which technology dominates the system. These visual cues make it easier to locate the current or potential regime of the system depending on the environmental assumptions.

These results confirm the relevance of including the GWP_{op} of non-dominant energy carriers in the analysis. While gasoline cars may appear to be a robust solution, their dominance proves to be sensitive to relatively low GWP_{op} values. Yet, the critical thresholds identified in Table 3.10 remain fully consistent with the orders of magnitude reported in the literature. According to Rai et al. [64], the GWP_{op} of a fuel is around 0.097 kg CO_2eq/kWh. These emission levels can therefore not be considered extreme, which further highlights the vulnerability of certain thermal technologies under realistic environmental constraints.

3.6.3 Critical thresholds and identified transitions

To identify the critical thresholds specific to private mobility, we used the GWP_{constr} values from the EnergyScope input data, as provided in the official documentation [43]. In contrast to the dominance-based approach, which can lead to cascading effects, the aim here was to isolate and understand the specific GWP values at which technologies become dominant or disappear from the mix.

The methodology applied is identical to that described in Section 2.4. However, in the case of private mobility, the system is typically dominated by a single technology at a time. This strong dominance limits the identification of certain thresholds: each emergence is immediately followed by full dominance and each loss of dominance results in complete disappearance. No intermediate state was observed.

The thresholds identified for each technology, along with their current GWP_{constr} values defined for each technology family are summarized in Table 3.11 below.

Technologies	Current value	ET = RTP	TP = POT
FCEV	786	366 (-53 %)	X
HEV	519	359 (-31 %)	X
BEV	385	X	X
Car diesel	342	X	492 (+44 %)

Table 3.11: Critical transition thresholds identified for the main private mobility technologies. The values correspond to the GWP_{constr}, expressed in kt CO_2eq/Mpkm/h. The columns ET= RTP and TP = POT respectively indicate the emergence/dominance points and the tipping/phase-out thresholds, when observable.

Among biofuel-based technologies, automotive diesel immediately becomes dominant, while automotive NG and automotive methanol are eliminated, probably due to the penalty associated with their GWP_{op}, despite their lower investment costs. Interestingly, car gasoline has a GWP_{constr} equivalent to car diesel, yet it remains absent from the mix. This could be explained by its lower energy efficiency: a larger quantity of gasoline is required to deliver the same service as diesel.

Regarding hybrid technologies, HEV is selected by the system over PHEV, likely due to its lower investment cost.

The case of BEV is more difficult to interpret. Despite a moderate investment cost and a reasonable GWP_{constr} value, this technology is never selected. One possible explanation is that, although electricity is considered neutral in terms of GWP_{op}, its full carbon footprint is shifted toward the electricity production technologies. This could hinder the electrification of the private mobility sector, an observation worth exploring further in the broader discussion.

Finally, in simulations based on the documentation values, it was not possible to reproduce the gradual dynamic observed in the dominance-based approach. In fact, directly injecting these values leads to a massive favoring of car diesel, which bypasses the usual alternation sequence between FCEV and hybrid vehicles previously observed. Here, dominance is directly taken by diesel vehicles, without a transitional phase involving hydrogen-powered vehicles.

Nevertheless, a logical trajectory is observed once this initial dominance is established:

- Starting from 492 kt CO_2eq/Mpkm/h, car diesel is replaced by HEV;
- When the GWP of HEV reaches 539 kt CO_2eq/Mpkm/h, the technology disappears and diesel vehicles return.

This pattern remains consistent with the orders of magnitude identified in the dominance-based approach, although the sequence and timing of technology appearances differ significantly due to the higher starting GWP value of FCEV.

3.6.4 Indirect effects of private mobility on other thechnologies

The private mobility sector, unsurprisingly, exerts an indirect influence on the two other transport sectors: public mobility and freight. This section analyzes how variations in the GWP_{constr} of private mobility technologies affect the stability, dominance and substitution dynamics in these adjacent sectors.

Public mobility sector

Not all private vehicle technologies have the same impact on the technological mix of the public sector. The reference scenario, based on the GWP values provided in the input documentation, results in a clear hierarchy of dominant technologies: train, hydiesel bus and tramway.

However, when the GWP_{constr} of certain private mobility technologies such as BEV, FCEV, or hybrids is reduced, this ranking changes. The tramway then rises to second place, pushing the hydiesel bus to third. This order remains relatively stable regardless of the level of GWP_{constr} reduction applied.

Figure 3.24 shows the effects of the cascading increase in the GWP_{constr} of thermal and hybrid cars.

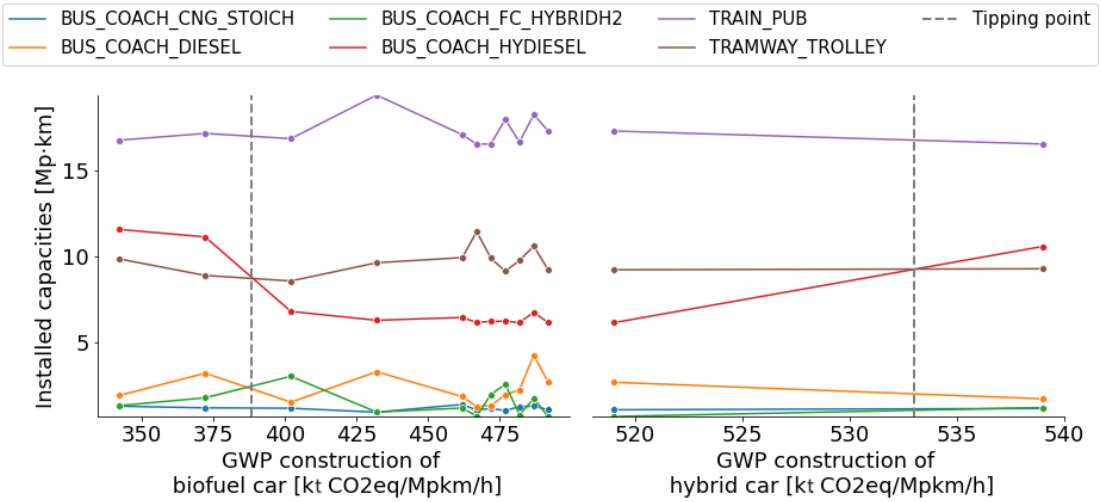


Figure 3.24: Evolution of installed capacities in the public transport sector as the GWP_{constr} of biofuel cars and then hybrid cars increases. The first marked transition (left dashed line) corresponds to the switch between tramway and hydiesel bus, as observed in the top 3 analysis. The final stabilization (right dashed line) reflects the reallocation of resources as private hybrid cars become less competitive.

When the GWP_{constr} of thermal cars is gradually increased, the dominance ranking remains consistent with the reference scenario until the GWP_{constr} of thermal vehicles decreases by 13 %. At this point, the tramway moves into second place, pushing the hydiesel bus down to third.

Continuing this cascading logic with an increase in the GWP of hybrid vehicles triggers a new shift: when the thermal car increases by 44 % and the hybrid increases by 2.5 %, the hydiesel bus regains second place, relegating the tramway once again to third.

This alternation reflects systemic effects of resource reallocation. When hybrid cars become uncompetitive, the associated resources are redistributed, favoring the return of the hydiesel bus in the public mobility mix.

Finally, stabilization of the public sector is observed when the GWP_{constr} of thermal vehicles becomes high. The ranking of technologies tends to settle, reducing transitions and making the system more robust. A comparable phenomenon will be observed in the freight sector.

Freight sector

The freight sector is primarily dominated by diesel trucks, whose position remains generally stable and by diesel boats, which exhibit more variability.

When the GWP_{constr} of private mobility technologies is increased, several indirect effects emerge. Reducing the GWP of electric or hydrogen vehicles induces an alternation between diesel trucks and diesel boats, as shown in Figure 3.25, while FCET retain a certain level of variability, as already observed in Section 3.5.7.

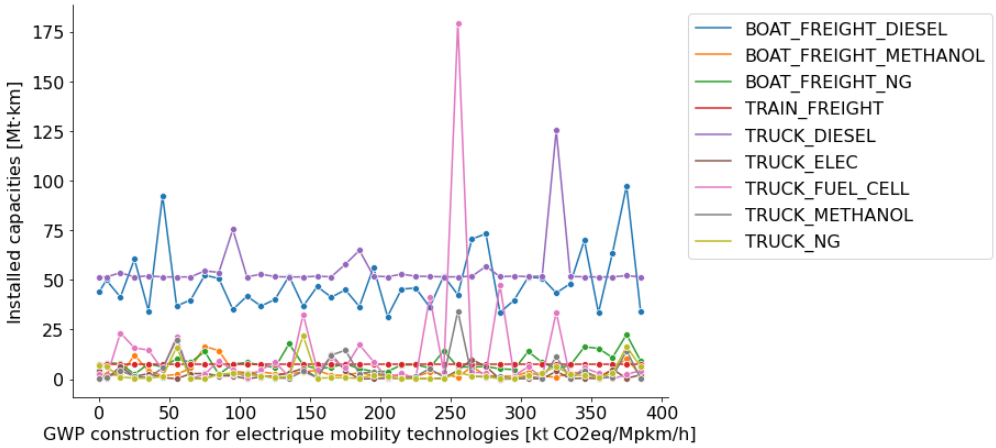


Figure 3.25: Installed capacities of freight technologies as a function of the GWP_{constr} of electric mobility technologies. Most technologies remain relatively stable, except for FCET and boat freight diesel, which show spikes and occasional variations.

When the GWP of hybrid cars is decreased, these alternations are reduced: diesel trucks become significantly more stable compared to diesel boats, whose variability is also softened.

Figure 3.26 shows the effect of the cascading increase in the GWP_{constr} of thermal cars followed by hybrid cars.

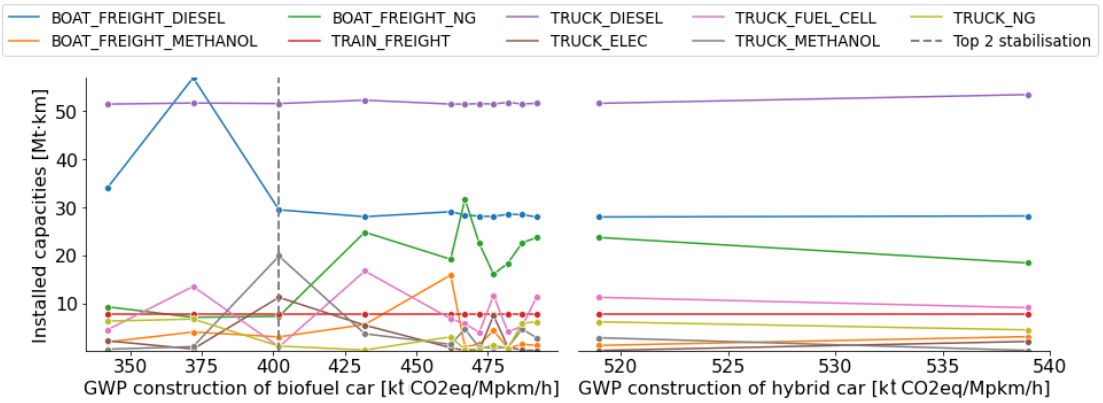


Figure 3.26: Evolution of installed capacities in the freight sector in response to the increasing GWP_{constr} of biofuel cars and then hybrid cars. A progressive stabilization of truck diesel and boat freight diesel is observed, reflecting a reallocation of energy vectors towards heavy-duty uses as private cars become less competitive.

The increase in the GWP_{constr} of thermal cars further stabilizes the ranking of technologies: diesel trucks reinforce their leading position and diesel boats stabilize in second place once the GWP_{constr} of thermal vehicles increases by 17 %. The same stabilization phenomenon is observed in the freight sector following the increase in GWP_{constr} of thermal cars and during the increase in GWP_{constr} of hybrid cars.

However, this redistribution of the gas vector leads to increased variability of the NG boat, following a mechanism similar to the one observed in the public sector: the reduced attractiveness of gas in private mobility makes it more available for other uses, locally shifting technological balances.

Increasing the GWP_{constr} of thermal cars in the private mobility sector led to a marked stabilization of technologies in freight and public transport. This is due to the release of biofuels for heavy-duty uses once thermal cars become less competitive, reducing competition for resources and allowing the system to settle into more stable configurations.

3.6.5 Stochastic analysis of private mobility

After considering significant or extreme variations in GWP using a deterministic approach in the previous sections, this section explores a second approach: stochastic analysis.

In this analysis, realistic values for the GWP_{constr} of private vehicles were extracted from the official documentation [43] and manually integrated into the design space. Unlike the default EnergyScope TD model, where these values are set to zero, each parameter was subjected to a uniform variation of $\pm 20\,\%$ around its nominal value [54].

The objective is twofold:

- to observe internal variations within the private mobility sector, particularly regarding the stability or instability of the dominant technology;
- to identify systemic effects induced in other sectors, especially freight, public mobility and storage, linked to the redistribution of energy carriers.

Direct effects on private mobility

The boxplots shown in Appendix E confirm that most private mobility technologies are only weakly affected by these variations. The only ones showing notable changes are diesel, natural gas and gasoline cars, which are also the only technologies to appear significantly in the mix in most runs.

The dynamic observed is one of intra-family substitution among these three thermal technologies: when the GWP_{constr} of the diesel car increases, it is replaced by the natural gas or gasoline car, depending on which has the lowest GWP_{constr}. The methanol car, although part of the same family, never appears as dominant likely due to its higher GWP_{op}.

The Sobol indices in Figure 3.27 confirm the expected influence hierarchy. The most influential parameter is the GWP_{constr} of the diesel car, with an index of 0.58. It is followed by the gasoline car (0.22) and the NG car (0.1). Other technologies show negligible indices, which corroborates their minor role in the observed variations.

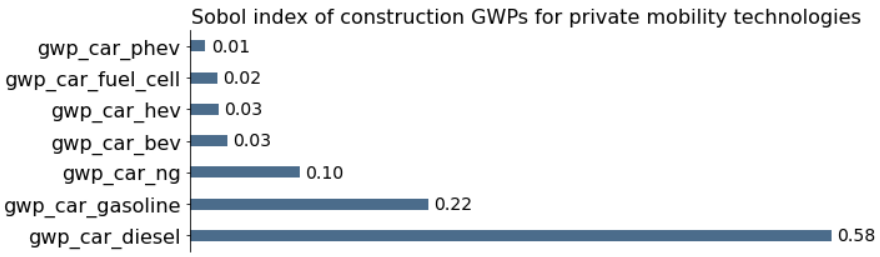


Figure 3.27: Sobol indices associated with the GWP_{constr} of private mobility technologies. The diesel car dominates clearly, with an index of 0.58, followed by the gasoline car at 0.22 and the NG car at 0.10. The other technologies exhibit a negligible influence on the results.

Observed systemic effects

Variations in the GWP_{constr} of private mobility technologies lead to indirect effects in other sectors of the system, as illustrated by the correlation matrix in Figure 3.28.

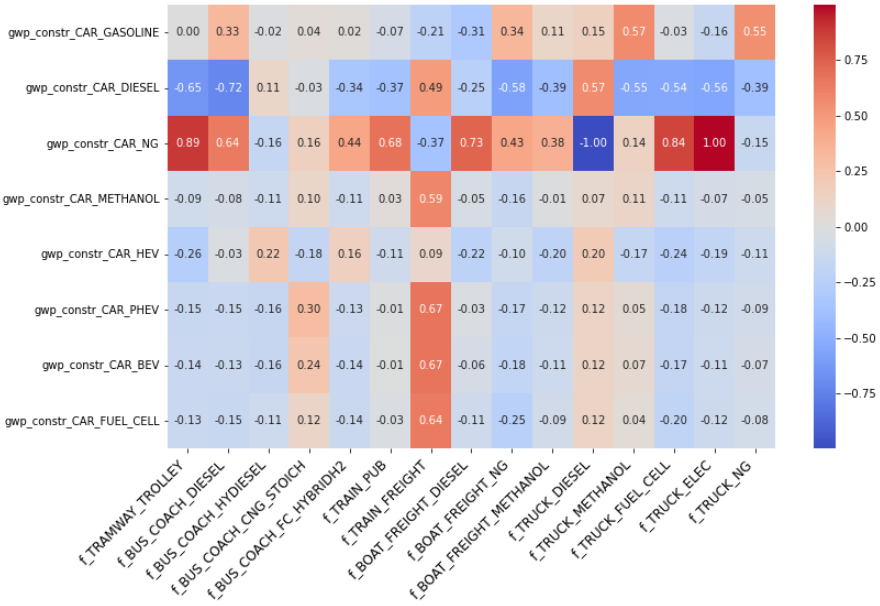


Figure 3.28: Correlation matrix between the GWP_{constr} of private vehicles and the installed capacities of public and freight mobility technologies. A positive correlation is observed between the GWP_{constr} of private cars and technologies in other sectors that rely on the same energy vectors, confirming the systemic stabilizing effect discussed earlier.

The most sensitive technologies are indeed those that appear in the technology mix results, namely diesel cars, NG cars and gasoline cars. Correlations with other technologies remain generally weak, except in cases related to resource reallocation in the freight sector.

One of the clearest examples is the increase in the GWP_{constr} of diesel cars, which favors the use of diesel trucks, while the increase in NG car GWP_{constr} reinforces the installed capacity of NG freight boats. This latter phenomenon illustrates a redistribution of the energy vector: when thermal cars become less competitive, biofuels are freed up for other uses, in this case, maritime freight.

Contrary to expectations, the public mobility sector is not entirely unaffected. The correlations reveal a certain sensitivity of the tramway and passenger train to variations in the GWP_{constr} of thermal cars, particularly biofuel cars. This confirms the findings from the deterministic top 3 analysis, where alternation between tramway and hydiesel bus was observed depending on the competitiveness of natural gas cars.

A notable result emerges in the extended matrix including storage technologies, available in Appendix E: a significant positive correlation of 0.6 between the GWP_{constr} of gasoline cars and the installed capacity of methanol storage. This suggests that when gasoline cars become less competitive, the methanol vector is more strongly mobilized in the system, potentially as a buffer storage or fallback solution. Although systemic, this effect remains localized and would warrant more detailed investigation.

Global interpretation

Overall, the results show that the effects of stochastic uncertainties on the GWP_{constr} of cars are generally limited within the modeled system. Dominance in the private mobility sector remains relatively stable under a $\pm 20\,\%$ variation and repercussions on adjacent sectors remain moderate.

However, the analysis highlights two important points. First, internal substitutions among thermal vehicles remain sensitive to environmental variations.
Second, the reallocation of energy carriers can induce indirect effects in sectors that consume those resources, particularly freight and public mobility.
Finally, the low standard deviation in total GWP results approximately $1\,\%$ confirms that the uncertainties tested here do not challenge the overall carbon footprint of the system, but can locally alter certain technological configurations.

Chapter 4

Discussion

This discussion puts the results obtained into perspective with respect to the five research questions defined in the introduction, comparing them with the insights from the literature and highlighting the main dynamics revealed by the analysis.

4.1 Impact of integrating the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies into the optimized results

Several studies have shown that it is possible to integrate embodied emissions into 2050 energy scenarios by coupling LCA with optimization models. Although generally less significant than operational emissions, these embodied emissions can, when explicitly considered, alter optimal technological choices [8].

In this work, the explicit integration of the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies into the environmental constraint of EnergyScope TD significantly changes the optimal configuration of the Belgian energy system in 2050. In the reference scenario, shifting from an objective of minimizing only $\mathrm{GWP}_{\mathrm{op}}$ to minimizing total GWP reveals that $\mathrm{GWP}_{\mathrm{constr}}$ already account for 57 % of total emissions, even before including those associated with storage and mobility. This finding illustrates the substantial weight of embodied emissions in energy infrastructures and confirms the necessity of considering them in the design of low-carbon pathways.

When the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies is further added to the environmental constraint, several adjustments occur in the optimized mix. Gas storage disappears entirely likely due to its high $\mathrm{GWP}_{\mathrm{constr}}$ and only reappears after a drastic reduction of about 87 %. Conversely, some technologies show remarkable stability, such as PHS, high-temperature storage, electric heat pumps and lithium-ion batteries, which remain present in most configurations. In private mobility, this consideration

also leads to the disappearance of BEV, replaced by FCEV, HEV, or internal combustion vehicles depending on the input conditions. This substitution is partly explained by an initial imbalance in the data: the GWP_{constr} of battery is known and therefore penalized, whereas that of other drivetrains, as well as the GWP_{op} of the vectors they use, was not initially taken into account. Even after correcting this bias, BEV do not regain their dominant position, showing that the constraint on the GWP_{constr} of storage indirectly influences choices in other sectors.

These changes highlight a central point: storage is only one of the system's flexibility levers, alongside other strategies, notably synthetic fuels [52]. When the GWP_{constr} of storage is increased without simultaneously modifying the GWP_{op} of other levers, particularly biofuels and imported gases, the model tends to rely more on these unconstrained vectors. This results in a phenomenon of emissions externalization: the reduction of the national carbon footprint then comes at the cost of increased emissions in supplying countries. Such a situation biases conclusions on optimal choices and obscures the actual global environmental impacts.

When this bias is corrected by simultaneously accounting for the GWP_{op} of imported vectors and the GWP_{constr} of storage, the system regains a more coherent balance. The results then come closer to those of the **Min cost** scenario, while retaining notable differences, such as the persistence of certain drivetrains' dominance in private mobility or the occasional emergence of methanol storage as a buffer solution.

Finally, since storage is not a final use, its installed capacity tends to decrease as its GWP_{constr} increases, until it stabilizes around a core of robust, low-impact technologies. These results show that taking embodied emissions into account, even when limited to storage technologies, does not simply reduce the share of high embodied-carbon solutions: it also alters intersectoral balances, challenges some solutions presented as universally optimal, such as massive electrification and underlines the need for a systemic approach integrating all flexibility levers to avoid emission-shifting effects.

4.2 Influence of uncertainty on the robustness of the energy system

In energy models, uncertainty can concern many parameters, such as costs, performance, or resource availability. Rixhon [68] identify nine main groups, ranging from import prices and investment or maintenance costs, to the potentials and capacity factors of renewables, the availability of limited resources, the

distribution of final demands and other structural assumptions such as the discount rate or the evolution of modal shares.

In this work, the stochastic analysis focuses on a single family of parameters: the GWP_{constr} of storage technologies. Even when considering a relative variation of 75 %, the impact on the system's total GWP remains limited, with a standard deviation below 1 %. However, this low overall sensitivity should not mask significant sectoral effects, which can redirect technological choices and the trade-offs between energy carriers.

A detailed correlation analysis shows that the influence of uncertainty depends both on the storage technology concerned and on the final-use sector. Methanol storage and high-temperature storage display similar behaviours: an increase in their GWP_{constr} reduces their attractiveness in the mix, prompting the model to mobilize other solutions, often less electric, in high-temperature heat, while reinforcing, through a substitution effect, electrification in freight mobility. Conversely, seasonal storage mainly affects public transport, whose electrification is favoured when its GWP increases. In other words, it is not storage that directly affects the electrification rate, but the technological reallocation it triggers in the system, which subsequently modifies the relative share of electric and non-electric solutions in each sector.

These sectoral effects are compounded by intersectoral repercussions. For example, an increase in the GWP of high-temperature storage tends to encourage modal shift from rail to diesel road transport for freight, to favour gas boilers over electric ones for high-temperature heat and to increase reliance on gas or methanol storage at the expense of renewable ammonia. Similar trends are observed with methanol storage, highlighting that a localized variation in storage can lead to a reorientation of technological trade-offs across several sectors simultaneously.

The strong dependence of electrification pathways on the GWP value assigned to certain storage technologies implies that underestimating or overestimating this parameter could steer the system towards a radically different technological regime. Such shifts can affect not only the level of electrification, but also import flows, mobility choices and cross-sectoral interactions. This confirms that storage must be regarded as a central lever in transition scenarios, whose environmental robustness depends as much on its direct impacts as on its interactions with other system components.

Ultimately, the robustness analyses show that uncertainty over the GWP_{constr} of

storage technologies has little influence on overall environmental performance, but can play a decisive role in shaping sectoral trajectories, particularly in mobility, freight and certain industrial applications. The relatively small magnitude of this global impact explains why no dedicated prospective analysis has previously been conducted on this specific parameter. Nevertheless, having realistic orders of magnitude remains essential: this prevents artificially placing all technologies on an equal footing when their actual environmental performance may differ significantly.

4.3 Critical GWP thresholds leading to the disappearance or dominance of a technology

The analysis of critical thresholds was carried out in two distinct sectors: storage and private mobility. The objective is to identify the GWP_{op} or GWP_{constr} beyond which a technology completely disappears from the optimized energy mix or, conversely, becomes dominant in its sector. In the storage sector, this analysis highlights the tipping points specific to each technology and their substitution relationships. In the private mobility sector, it sheds light on the sensitivity of drivetrains to variations in the environmental impacts associated with their energy carriers and key components.

4.3.1 Storage sector

The tipping point analysis shows that certain storage technologies have critical GWP values beyond which they disappear from the energy mix or, conversely, become dominant. These thresholds reflect relative competitiveness shifts between solutions providing similar functions and can trigger major reallocations within the storage portfolio.

The case of gas storage is particularly illustrative: it disappears as soon as its GWP_{constr} is integrated into the environmental constraint and only reappears if this value is reduced by 87 %. Daily storage shows similar behaviour, being competitive only in the event of a drastic reduction in its GWP_{constr} (-97 %). These results indicate that a targeted reduction of these parameters would allow these technologies to reach their appearance threshold and improve their competitive position in the mix.

Conversely, some technologies such as PHS, electric heat pumps and high-temperature storage have very high critical thresholds, sometimes unattainable under the simulated realistic conditions, confirming their high stability. Seasonal storage only disappears when its GWP_{constr} is multiplied by five, whereas lithium-ion

batteries remain relatively stable but with a more accessible threshold, a simple doubling is enough to exclude them from the mix. In the specific case of electric heat pumps, this stability is consistent with the findings of *PATHS2050 | Energy outlook* [59], which conclude that decentralised heat is mostly supplied by heat pumps, making their presence logical and structurally robust in a decarbonised system. Some technologies never drop to zero, such as PHS, which reflects either structural stability or persistence due to the absence of direct competition.

Other options exhibit clear emergence dynamics. Methanol storage, absent from the reference scenario, appears in the **Min gwp** scenario and sees its installed capacity grow in **Min gwp corr**, particularly when the GWP_{constr} of dominant technologies such as seasonal or high-temperature storage increases. This behaviour illustrates its role as a "buffer solution": it takes over when traditional storage pillars are penalised. Hydrogen storage shows a similar profile but remains unstable and quickly disappears if its relative competitiveness declines. Moreover, renewable methanol could play a pivotal role in the energy transition as a low-carbon fuel, a hydrogen carrier and a storage/transport solution, facilitating the shift from a fossil-based system to a renewable and hydrogen-based decarbonised system [32].

Substitution relationships between technologies also reveal specific thresholds. Seasonal storage and lithium-ion batteries have an asymmetric relationship: a change in the battery triggers an adjustment in seasonal storage, but not the reverse, confirming the central role of the latter. When the GWP_{constr} of lithium-ion batteries exceeds around 110 kg CO_2eq/kWh, methanol storage takes over, while a 35 % reduction decreases the share of electric heat pumps. Similarly, reducing PHS to its minimum limit favours lithium-ion batteries. High-temperature storage is substituted by methanol storage when its GWP_{constr} exceeds 88 kg CO_2eq/kWh, without any notable reverse effect. Furthermore, seasonal storage, methanol storage and hydrogen storage influence biofuel storage, reflecting possible substitutions in liquid fuel supply chains.

The integration of GWP_{op} modifies certain critical thresholds. Seasonal storage and electric heat pumps initially disappear due to the combined effect of penalising the GWP_{constr} and the bias of outsourcing towards imports, but reappear as soon as the GWP_{op} of gases increases. Lithium-ion batteries strengthen their position when the GWP_{op} of imported renewable vectors is strongly increased, benefiting from the loss of competitiveness of these latter. Methanol storage is also favoured by an increase in the GWP_{op} of hydrogen or methanol itself but loses this advantage when ammonia or hydrogen are heavily penalised. The behaviour of methanol and ammonia thus appears particularly dynamic with respect to increases in their

GWP_{op}, confirming their potential role as strategic levers in a decarbonised energy system. These results illustrate that an increase in the environmental cost of a vector can, in some cases, make it more attractive to store it rather than import it directly.

Finally, some technologies never cross an appearance point, even when the GWP_{constr} of their competitors is multiplied by ten or theirs is reduced to zero. This lack of sensitivity reflects structural non-competitiveness or the presence of systematically more efficient alternatives, as is the case for most decentralised thermal storages and certain biofuel storages.

In summary, crossing certain GWP values triggers cascading effects, altering the use of energy carriers, electrification and import trade-offs. The results also show that the behaviour of methanol and ammonia is highly dynamic with respect to increases in GWP_{op}, confirming their potential role as strategic levers in a decarbonised energy system.

4.3.2 Private mobility sector

The tipping point analysis for private mobility highlights a sector characterised by strong alternation of dominance and low technological stability. Transitions generally do not occur gradually: the mix shifts from one dominant technology to another without intermediate compromises.

The emergence of BEV remains extremely rare and occurs only under very specific conditions: the GWP_{constr} of FCEV, HEV and gasoline vehicles must respectively exceed around 610, 570 and 550 kt CO_2eq/Mpkm/h, while that of BEV must remain minimal. Except in this extreme case, BEV are not selected and, since the integration of the GWP_{constr} into the environmental constraint, private mobility is no longer electrified. This result contrasts with the projections of *PATHS2050 / Energy outlook* [59], which identify electric vehicles as the dominant option in light mobility, but is explained here by the fact that the full carbon footprint of electricity is attributed to the electricity production technologies, thereby reducing its attractiveness for this sector.

FCEV become competitive when their GWP_{constr} decreases by about 53 %, while HEV require a 31 % reduction to prevail over alternatives. Conversely, diesel vehicles lose competitiveness if their GWP_{constr} increases by about 44 %.

In the biofuel category, diesel cars retain an advantage over natural gas and methanol alternatives, penalised by higher GWP_{op}. Gasoline cars are excluded due

to their lower efficiency. In the hybrid category, HEV dominate PHEV mainly due to lower investment costs; the latter never appear in the results, even in extreme scenarios.

A notable systemic effect appears when the GWP_{constr} of internal combustion vehicles increases: this change leads to a marked stabilisation of technologies in the freight and public mobility sectors. This phenomenon is explained by interdependencies in the allocation of energy carriers. As long as combustion cars remain competitive, they capture a significant share of biofuels, creating pressure on the freight and public sectors, which are also major consumers of these resources. This observation is consistent with the conclusions of *PATHS2050 | Energy outlook* [59], which highlight intersectoral competition for access to biofuels. Conversely, making combustion cars less competitive frees up these carriers for heavy-duty uses, allowing the system to converge towards more stable and robust configurations.

These interactions are also reflected in the dynamics specific to the public and freight sectors. Diesel trucks remain generally stable, diesel ships show slight variability, while FCET remain highly unstable. A 17 % increase in the GWP_{constr} of biofuel cars stabilises the freight hierarchy, with diesel trucks in first place and diesel ships in second. This stabilisation effect is also linked to the lack of competition for certain dominant technologies, which explains why variations of around 20 % in private mobility do not strongly affect the observed dominance. Stochasticity finally confirms the granularity limit of the private mobility sector and the resulting reallocation of energy carriers.

Ultimately, the aim is not to determine a technology that will systematically dominate the system, but rather to identify those that, in a given context, are most likely to prevail. Without considering GWP_{op} and GWP_{constr}, dominance goes to FCEV, which remains true when all GWP_{op} of imported resources are considered. An increase in the GWP_{op} of dominant gases favours gasoline cars, while that of non-dominant gases benefits HEV. When GWP_{op} and GWP_{constr} are integrated simultaneously, dominance shifts to diesel cars. BEV prevail only in scenarios where the optimisation objective is cost minimisation rather than emissions minimisation, while PHEV never find a favourable context to impose themselves sustainably.

Cross-sector conclusion: Storage and private mobility

In summary, the critical threshold analysis shows that, in both storage and private mobility, a targeted variation of the GWP can trigger rapid shifts in dominant technologies, with cascading effects on other sectors. Some options, such as high-temperature storage or internal combustion vehicles, play a pivotal

role, while others act as buffer solutions. Intersectoral interactions, particularly through competition for biofuels, underline the need to integrate GWP_{constr} and GWP_{op} simultaneously in order to anticipate resource reallocations and ensure the robustness of transition pathways.

4.4 Effect of accounting for the GWP_{op} of imported energy carriers

Imported renewable energy carriers, such as methanol, ammonia, methane, or synthetic hydrogen, generally have a much higher cost than their fossil equivalents. For example, imported renewable methane is about 3.4 times more expensive than imported natural gas in the reference scenario [69]. This cost difference limits their competitiveness, so that in cost-minimising configurations, imports are installed only in limited capacity, particularly when climate constraints are weak. However, in a fully decarbonised system, their high average price and significant variability make them one of the most influential parameters on the total annual cost, with an impact of up to 53.2 % [69].

From an environmental perspective, even if domestic production of these carriers does not generate direct emissions, their import must be evaluated on a global scale. Foreign production processes can generate significant emissions and the primary resources mobilised are not always carbon-neutral. Data from several sources [9, 45, 78] show that the GWP_{op} of biofuels and other renewable carriers vary widely, from 0.01 kg CO_2eq/kWh to more than 0.2 kg CO_2eq/kWh, depending on the type of carrier and the production process used. The values adopted for this work fall within this range and are consistent with the orders of magnitude reported in the literature, but they would benefit from being refined through a specific assessment of the uncertainties associated with each carrier. The final GWP_{op} values used for the main imported energy carriers are presented in Table 4.1, forming the basis for the previous analyses.

Resources	GWP_{op} [kg CO_2eq/kWh]
Méthanol RE	0.11
Ammoniac RE	0.07
Gaz RE	0.10
Hydrogène RE	0.09
Bioéthanol	0.06
Biodiesel	0.06

Table 4.1: GWP_{op} for the main imported energy carriers. Values are expressed in kg CO_2eq/kWh and correspond to the assumptions used in the optimisation scenarios, including the utilisation phase of the imported resources.

When the objective becomes minimising emissions without taking into account the GWP_{op} of imports, certain imported renewable vectors, available in unlimited quantities, are favoured. This is particularly the case in private mobility, where FCEV dominate due to the absence of a significant GWP_{constr} for this type of vehicle, unlike BEV, which are penalised by the carbon footprint of their batteries. The absence of an environmental constraint on imports therefore creates a systemic bias in the optimised mix.

Integrating the GWP_{op} of imports reduces the competitiveness of these carriers and reorients the system towards local production and storage. In some cases, it then becomes more advantageous to produce a carrier locally and store it rather than importing it directly.

Hydrogen storage clearly illustrates this dynamic: in the **Min cost** scenario, it is reinforced because it supports local hydrogen use by providing additional flexibility. In contrast, in **Min gwp**, it disappears in favour of a strategy consisting of importing hydrogen in the form of ammonia and reconverting it locally at the point of use, thus eliminating the need for a pressurised storage infrastructure. In **Min gwp corr**, some carriers such as LFO, diesel, gasoline, or ammonia continue to be stored locally despite the increase in their GWP_{op}, as this option remains more competitive than direct import.

The impact of this reorientation is also measurable at the system level: in **Min gwp** without accounting for the GWP_{op} of imports, primary resource consumption is 40 % higher than in a system that includes it, indicating suboptimal allocation and lower energy efficiency. Integrating GWP_{op} corrects this outsourcing bias by significantly reducing imports and strengthening the system's resilience through the development of local production and storage capacities.

Finally, so-called non-dominant energy carriers such as bioethanol or biodiesel must also be penalised. Their low, or even zero, initial GWP_{op} can artificially favour their import over more relevant local alternatives.

Ultimately, accounting for the GWP_{op} of imported carriers profoundly changes the trade-offs between storage, electrification and imports. It favours a more balanced mix, reduces external energy dependence, concentrates electrification on strategic uses and limits the outsourcing of emissions beyond the national boundary.

4.5 Interactions between storage, mobility and imports

The joint analysis of the storage, mobility and import flow sectors highlights structural links that are decisive for technological trajectories in optimised energy systems. These interactions often manifest indirectly: a change in competitiveness in one sector affects the others through the reallocation of energy carriers and the adjustment of environmental constraints.

The evolution of the freight sector clearly illustrates the magnitude of intersectoral effects. In the reference scenario, FCET occupied the leading position. However, the simultaneous integration of the GWP_{constr} for storage technologies and the GWP_{op} of imported resources shifted this dominance towards electric trucks, reflecting a change in electrification priorities. While private mobility initially focused electrification efforts, freight, which is only 9 % electrified in the reference scenario, is now becoming the priority sector.This sectoral reallocation shows similarities with the orientations described in *PATHS2050 / Energy outlook* [59], where maritime freight relies mainly on methane or ammonia and short-distance trucks on electricity.

This redistribution of electrification also results from structural constraints. Faced with the limited potential of domestic renewable energies and the low capacity to import electricity, the model cannot massively electrify all sectors. It therefore prioritises uses offering the best economic and energy efficiency in electricity conversion. Several factors thus hinder the rise of electric vehicles: limited availability of imported electricity, capacity factor and caps imposed on installed photovoltaic and wind capacities [69].

In this new context, FCET act as a "buffer technology": rarely dominant, they appear opportunistically when the main options temporarily lose competitiveness. Their recurring presence in unstable situations reflects high environmental

elasticity, ie increased sensitivity even to moderate variations in environmental parameters.This instability is particularly pronounced when the GWP_{constr} of lithium-ion batteries varies: at its current value, a significant peak in FCET usage is observed, but a variation of less than 10 % is enough to trigger a marked decline. This shift is reinforced by the fact that before the addition of GWP_{op}, freight was largely dominated by FCET, whereas it is now oriented towards electric trucks.

The correlations identified between sectors confirm the existence of structural links. For example, a positive correlation of 0.6 is observed between methanol storage and the GWP_{constr} of gasoline cars. This link may be explained by the fact that, in certain scenarios, methanol vehicles capture around one-third of the demand when complementing a fleet dominated by gasoline cars. This phenomenon illustrates how adjustments in private mobility can indirectly influence the demand for the storage of certain carriers and, by extension, the trade-offs between import and local production.

These results emphasise that optimal trade-offs can only be understood through an integrated approach: technological choices in storage modify the allocation of energy carriers, which reconfigures the relative competitiveness of mobility options and redefines the level of dependence on imports.

Key takeaways

The results show that it is necessary to integrate the GWP_{constr} into energy system optimisation, but that this inclusion must go hand in hand with accounting for the GWP_{op} of imported carriers in order to avoid emissions outsourcing. The analysis confirms that electrification, although important, is not a universal solution and that mobility, whether private, public or freight-related, must also take into account emissions linked to construction in its assessment in order to avoid sub-optimal reallocation of resources. This work thus highlights the key technologies on which to focus efforts, as well as certain sectoral and intersectoral dynamics linked to the evolution of their environmental impact. Finally, it underlines the importance of the optimisation objective, as the comparison between cost minimisation and GWP minimisation reveals significant differences in the resulting trajectories.

Conclusion

Recommendations

The analyses conducted in this work lead to several concrete recommendations to guide energy planning and technological development priorities towards 2050. Each point below is directly based on findings from the simulations and sensitivity analyses.

- **Prioritise support for robust storage technologies**
  Finding: Certain technologies such as seasonal thermal storage, high-temperature storage, PHS, Li-ion batteries and electric heat pumps, maintain a competitive role in most scenarios, even when the $\mathrm{GWP}_{\mathrm{constr}}$ is taken into account. Others, such as gas storage or daily storage, appear in the mix only when their GWP is reduced.
  Recommendation: Strengthen the competitiveness of robust technologies by reducing their environmental impact and supporting their large-scale deployment. For technologies sensitive to GWP, target efforts at reducing their construction footprint to facilitate their integration.

- **Reassess the relevance of technologies absent from the mix**
  Finding: Some technologies, such as decentralised thermal storage (excluding heat pumps), never appear in optimised configurations, regardless of the parameter combination considered.
  Recommendation: Either conduct targeted research to improve their performance and reduce their GWP, or reallocate R&D and funding efforts towards more promising solutions.

- **Systematically integrate the $\mathrm{GWP}_{\mathrm{constr}}$ and the $\mathrm{GWP}_{\mathrm{op}}$ of imports into planning**
  Finding: Adding the $\mathrm{GWP}_{\mathrm{constr}}$ and the $\mathrm{GWP}_{\mathrm{op}}$ of imports does not massively alter the system as a whole, but reveals numerous intersectoral interactions and indirect effects on mobility and storage.
  Recommendation: Consider these parameters jointly, with realistic orders of magnitude, in prospective scenarios to anticipate their impacts, avoid biased decisions and ensure a coherent evaluation of environmental impacts.

- **Focus efforts on dominant technologies in private mobility**
  Finding: The most frequently dominant technologies are gasoline, diesel, HEV and FCEV, whereas BEV are absent in this work.
  Recommendation: Focus efforts on these identified dominant technologies and conduct further research on the potential of BEV, assessing them from the perspective of carbon neutrality rather than cost alone.

- **Adapt the electrification strategy according to the sector**
  Finding: Storage technologies strongly influence electrification levels. Contrary to many studies that prioritise electrification of private mobility, the results show that, under a strict objective of reducing total emissions, it is more strategic to electrify freight.
  Recommendation: Revise electrification policies by prioritising sectors where the climate impact is most reduced.

- **Consider methanol as a versatile solution**
  Finding: Methanol appears as a flexible carrier, able to play a role in storage, mobility, freight transport and certain non-energy uses.
  Recommendation: Investigate and support the development of low-carbon methanol as a buffer solution in an uncertain energy system.

- **Find an optimal balance between storage and imports**
  Finding: In a 100 % renewable system, production intermittency requires maximum flexibility. The results show that the balance between storage and imports is a key lever for reducing costs and emissions.
  Recommendation: Implement policies enabling dynamic adjustment of this balance based on resource availability and their GWP.

- **Avoid placing fuel-cell hydrogen as the dominant freight technology**
  Finding: Fuel cell trucks quickly lose their dominant position as soon as the GWP of different technologies in the system changes, revealing strong instability. Electric trucks, on the other hand, show greater stability in the face of such changes.
  Recommendation: Favour a larger share of electric trucks in freight, while keeping hydrogen as a complementary option.

Limitations and perspectives

Limitations

The explicit integration of GWP_{constr} within an intersectoral framework and the analysis of their effects on optimised technological trajectories come with limitations that are sometimes specific and distinct from those commonly encountered in prospective modelling.
They can be grouped into three categories, each point being accompanied by a potential improvement pathway.

Model and structure

- **Insufficient technological granularity**: Variations in GWP_{constr} were applied by technology families. This masks behavioural differences observed within the same family.
  Improvement pathway: assign distinct parameters to each technology, potentially through targeted adaptation of the EnergyScope TD input data.

- **Identical assumptions for certain technologies**: Some input assumptions are identical for several technologies, particularly in decentralised thermal storage, reducing the detection of real performance divergences.
  Improvement pathway: initially conduct dedicated studies to differentiate the GWP and other similar parameters, thereby increasing the granularity of the model. These differentiated assumptions should then be systematically integrated, even for similar technologies, in order to better reflect their specific behaviours.

- **Limited traceability of imported flows**: In EnergyScope TD, it is not possible to distinguish whether a consumed resource comes from domestic production or imports, nor to identify its final use by sector.
  Improvement pathway: integrate a traceability module differentiating local production from imports, with sectoral allocation.

- **Representation of storage in EnergyScope TD**: The model does not explicitly treat storage as a flexibility requirement. As a result, when the GWP_{constr} is high, storage capacities are mechanically reduced as if they could be easily replaced. This simplification can lead to oversizing the production system and increasing primary energy consumption to compensate for the lack of flexibility, thereby reducing the overall efficiency of the system.
  Improvement pathway: Explicitly integrate the flexibility requirement into the optimisation framework, for instance by introducing an efficiency index

defined as the ratio between total primary energy consumption and the actual final energy demand. This indicator would help identify oversizing situations caused by insufficient storage and guide the model towards an optimal balance between storage and imports.

- **Single time horizon**: The analysis is limited to 2050, without intermediate trajectories or assessment of short/medium-term resilience.
  Improvement pathway: use EnergyScope Pathways to model intermediate milestones and capture transitional effects [51].

Data and indicators

- **Uncertainties in LCA data**: The GWP values come from averages taken from the literature or databases, without accounting for regional, temporal, or process-related variations. These data were used as working assumptions to obtain a representative order of magnitude but do not replace the accuracy of complete life cycle assessments.
  Improvement pathway: conducting LCA studies specific to the technologies considered, based on detailed and up-to-date inventories, would strengthen the robustness and credibility of the results.

- **Limited environmental indicators**: The evaluation relies solely on GWP, whereas other impacts, such as biodiversity, acidification and soil and water pollution, can change the technological preference order [34].
  Improvement pathway: broaden to a multi-indicator LCA and integrate these criteria into a multi-objective optimisation, as is currently being developed in EnergyScope Multi-Criteria [51].

- **Unaccounted offshored emissions**: The GWP related to the foreign production of imported resources is excluded, which can artificially reduce the territorial balance.
  Improvement pathway: systematically include emissions generated abroad for global consistency and use EnergyScope Multi-Cells to explicitly represent exchanges between regions or countries [51].

Systemic interactions

- **Partially explored intersectoral effects**: The GWP of private mobility can influence other sectors such as public and freight mobility, but the parameters of these latter have not been modified, which can generate artificial reallocation effects.
  Improvement pathway: vary the parameters of several sectors simultaneously to capture cross-effects and limit biases linked to isolated modifications.

Perspectives

Beyond methodological improvements, three concrete applications directly emerge from the results of this work.

Exploring extreme scenarios to inform cost–climate trade-offs

Shifting the objective from minimising costs to minimising total emissions leads to a notable reconfiguration of technological choices, even if the overall system cost increases significantly. This approach provides decision-makers, beyond economically optimal scenarios, with configurations that maximise emission reductions, even at higher costs.
Comparing such extreme scenarios helps to identify realistic compromises between climate ambition and budgetary constraints, directly linked to the 2050 carbon neutrality target. This work also highlights the technologies that deliver the greatest emission reductions, enabling priority to be given to those whose deployment could ultimately help contain costs while maintaining high environmental performance.

Assessing the potential role of a full nuclear pathway

The analysis shows that full electrification of the system is not possible without massive imports, unless additional low-carbon generation is introduced.
An extension would consist of integrating the entire nuclear chain to test whether this option would make it possible to achieve 100 % carbon neutrality while reducing imports. The results would provide a quantified basis for a major strategic debate.

Testing the robustness of trajectories in crisis situations

The developed approach could also be used to assess the resilience of optimised configurations to severe disruptions for example, a sudden increase in import prices, a supply disruption, or the unavailability of key technologies.
Such shocks can act as real tipping points, leading to rapid and profound reorganisations of the energy system. Simulating such scenarios would make it possible to identify the most robust configurations and anticipate contingency plans, complementing the analyses under average conditions.

In summary, these perspectives pave the way for a broader use of the method, not only to refine models but above all to provide decision-makers with clear benchmarks on possible trajectories. By comparing extreme scenarios, controversial technological options and robustness tests, it becomes possible to design strategies aligned with carbon neutrality while taking economic constraints and supply security into account.

Conclusion

This master thesis developed a methodology to assess the influence of adding the GWP_{constr} of energy storage technologies, as well as their uncertainty, on the optimal planning of the Belgian energy system by 2050 using the EnergyScope TD model. The approach combines optimisation, stochastic analysis and tipping point studies, enabling the exploration of both average effects and extreme behaviours.

The results show that adding the GWP_{constr} of energy storage technologies significantly alters optimal trajectories: technological reallocations, changes in electrification and reconfigurations of storage uses confirm the structuring role of embodied emissions. While uncertainty has little impact on global indicators, it influences certain sectoral trade-offs, notably in thermal storage, mobility and energy imports.

Including only the GWP_{constr} of energy storage technologies without the GWP_{op} of imported renewable carriers creates a major bias, penalising one element while leaving the other artificially neutral. The GWP_{op} should therefore be considered for both dominant and non-dominant carriers to avoid favouring specific sectors. The same principle applies to mobility, which should integrate both the GWP_{op} and the GWP_{constr} for the three sectors (private, public, freight). Omitting this dual consideration distorts competition and can trigger major resource reallocations.

The private mobility sector appears particularly unstable, with the dominant technology choice highly sensitive to the inclusion or exclusion of certain emissions. Moreover, increased imports and reduced storage capacities degrade the system's overall efficiency by increasing the demand for primary resources.

By combining analytical rigour with a systemic approach, this work provides methodological and empirical contributions to the prospective evaluation of energy systems. The proposed framework, transferable to other contexts, offers decision-makers tools to design robust trajectories consistent with decarbonisation objectives and resilient to uncertainties. It also complements economic approaches by revealing often-overlooked systemic effects and can be applied to other technologies or regions to guide more balanced and sustainable energy planning decisions.

Appendix A

Assigned $\mathrm{GWP}_{\mathrm{constr}}$ values for storage technologies

A.1 Estimates of $\mathrm{GWP}_{\mathrm{constr}}$ for selected storage technologies

For the technologies listed below, $\mathrm{GWP}_{\mathrm{constr}}$ values had to be estimated through calculations. The details are provided below:

- For decentralised technologies, a water tank was assumed as the storage component [43]. Based on the technical datasheet [40], :
  - $\mathrm{GWP}_{\mathrm{constr}}$ of a water tank:

$$GWP = 0.294 \left[\frac{kgCO_2eq}{L}\right] \cdot 190[L] = 55.86 \quad [kgCO_2eq] \tag{A.1}$$

  - Thermal energy stored:

$$\frac{190 \cdot 4186 \cdot 45}{3600 \cdot 1000} = 9.94 \text{ kWh} \tag{A.2}$$

  - $\mathrm{GWP}_{\mathrm{constr}}$ expressed in kg CO_2eq/kWh:

$$\frac{5.86}{9.94} = 5.62 \quad \left[\frac{kgCO_2eq}{kWh}\right] \tag{A.3}$$

- For centralized daily thermal storage, large-scale hot water tanks are used [43]. The same database as in EnergyScope is employed [21].
  - Hot temperature: $T_{\mathrm{hot}} = 70\,^{\circ}\mathrm{C}$

- Cold temperature: $T_{\text{cold}} = 5\,^{\circ}\text{C}$
- Thermal capacity per liter:

$$E_{\text{stored, 1L}} = \frac{4186 \cdot (70 - 5)}{3600} = 0.0755 \text{ kWh} \tag{A.4}$$

- $\text{GWP}_{\text{constr}}$ per liter: 2.81 $\text{kgCO}_2\text{eq/L}$ [58]
- $\text{GWP}_{\text{constr}}$ per unit of thermal capacity:

$$\frac{2.81}{0.0755} = 37.2 \ \left[\frac{\text{kgCO}_2\text{eq}}{\text{kWh}_{\text{stored}}}\right] \tag{A.5}$$

- Decentralised electric storage technologies are approximated by electric water heaters [2] whose construction gwp is 97.66 $\left[\frac{kgCO_2eq}{kWh}\right]$:
  - Energy stored in an electric water heater:

$$E = \frac{m \cdot c \cdot \Delta T}{3.6 \cdot 10^6} = \frac{1000 \cdot 4186 \cdot (60 - 15)}{3.6 \cdot 10^6} = 52.325 \quad [kWh] \tag{A.6}$$

  - Emissions from construction:

$$240000 - \text{Use} - \text{Recycle} = 101568 \quad [kgCO_2eq] \tag{A.7}$$

- The seasonal thermal energy storage tank described in [65] is a water tank with a total volume of 15 180 m^3. It is designed to be fully charged at the end of summer and discharged during the winter heating season. This corresponds to one full charge-discharge cycle per year.
  - Installed thermal capacity of the storage:

$$E_{\text{stored}} = \frac{15\,180 \cdot 1000 \cdot 4186 \cdot 75}{3.6 \cdot 10^6} = 1\,323\,822 \text{ kW h} = 1\,323.8 \text{ MW h} \tag{A.8}$$

  - Total energy supplied over the lifetime of the system, ie 40 years :

$$E_{\text{delivered, total}} = 1\,323.8 \times 40 = 52\,953 \text{ MW h} \tag{A.9}$$

  - The article reports an amortized construction GWP of 22.12 kg CO_2eq/MWh delivered:

$$GWP_{\text{total}} = 22.12 \times 52\,953 = 1\,171\,318 \text{ kg } \text{CO}_2\text{eq} \tag{A.10}$$

– $\text{GWP}_{\text{constr}}$ per installed thermal capacity:

$$gwp_{\text{constr}} = \frac{1\,171\,318}{1\,323\,822} = 0.884\,\text{kg CO}_2\text{eq/kWh} \tag{A.11}$$

- To estimate the non-amortised greenhouse gas emissions from the construction of a salt cavern used for gas storage, we rely on data from a case study for hydrogen storage [42]. The reported GWP is 0.188 kg CO_2eq/kg of gas stored, amortised over the entire 50-year lifetime. To retrieve the non-amortised impact :
  - Total number of complete charging/discharging cycles over the 50 years [21] :
    - Working gas volume: 0.44×10^9 m^3
    - Extraction rate: 8×10^6 m^3 per day
    - Time to empty: $\frac{0.44\times10^9}{8\times10^6} = 55$ days per full cycle
    - Estimated number of full cycles: $\frac{365}{55} \approx 6.6$ cycles per year
    - Over 50 years: $6.6 \times 50 = 330$ cycles
  - Non-amortised GWP per kg of capacity is $0.188\times330 = 62.0$ kg CO_2eq/kg
  - Using an average Lower Heating Value (LHV) of 10.83 kW h kg^{-1} for natural gas [60] :

$$\frac{62.0\,\text{kg CO}_2\text{eq/kg}}{10.83\,\text{kW h kg}^{-1}} = 5.72\,\text{kg CO}_2\text{eq/kWh} \tag{A.12}$$

- For diesel storage, the value was estimated as follows:
  - Storage tank weight : 432.7 t [29]
  - The global warming potential of stainless steel is 2.9 kg CO_2eq/kg [86]
  - LHV of diesel is 12.06 kW h kg^{-1} [17]
  - Density of diesel is 0.91 kg L^{-1} [15]
  - $\text{GWP}_{\text{constr}}$ expressed in kg CO_2eq/kWh:

$$\frac{2.9 \cdot 432.7 \cdot 10^3}{12.06 \cdot 20 \cdot 10^6 \cdot 0.91} = 0.0057 \left[\frac{kgCO_2eq}{kWh}\right] \tag{A.13}$$

Appendix B

Technological dominance of the three scenarios studied

Figure B.1 below presents the top three dominant technologies in terms of installed capacity across the different scenarios analyzed:

- **Reference scenario**: cost minimization under a total emissions constraint of 10 Mt CO_2eq/year.
- **Min cost scenario**: same as the reference scenario, but including the GWP_{constr} for energy storage technologies.
- **Min gwp scenario**: GWP minimization under a cost constraint limited to 80 000 M€/y.

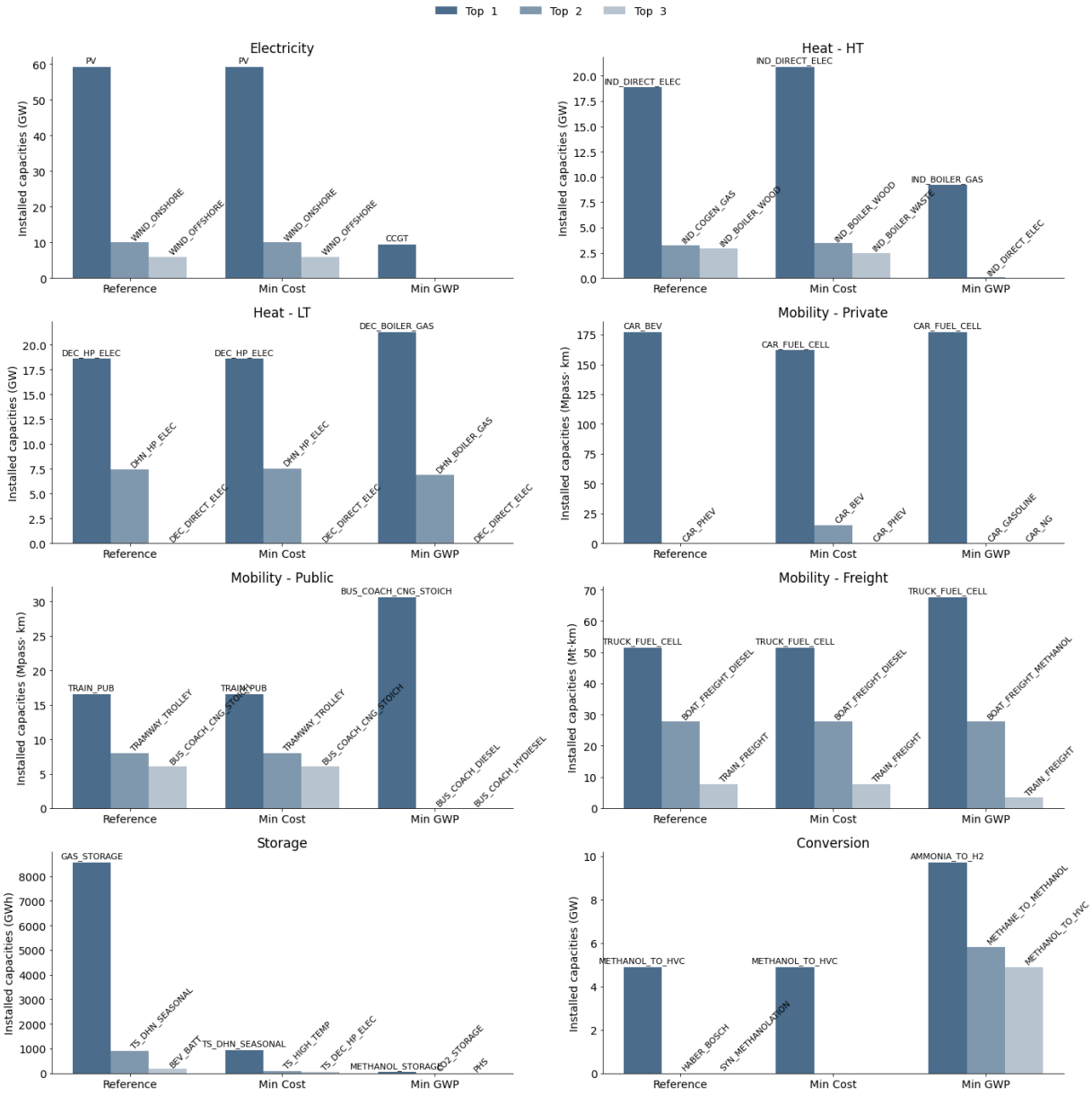


Figure B.1: Top three technologies by installed capacity across the eight main system components: electricity, heat (low and high temperature), mobility (private, public, freight), storage and conversion for the three studied scenarios. The values reflect the dominance of each technology class in the system architecture.

Appendix C

Corrected scenario

This appendix presents the detailed results of the **Min gwp Corrected** scenario. This scenario aims to minimize the total GWP of the Belgian energy system by 2050, under a budget constraint of 80 000 M€. It explicitly accounts for the GWP_{op} of dominant imported renewable resources, in order to better reflect their actual environmental impact.

The first section presents the deterministic results, highlighting the optimal technological configurations resulting from this reinforced environmental constraint. The second section reports the correlation outcomes of the stochastic analysis, assessing how uncertainty on the GWP_{constr} of storage technologies affects system-wide environmental performance.

C.1 Deterministic results and optimal system configuration

This section provides a detailed presentation of the results obtained for the **Min gwp corrected** scenario, including installed capacities by sector, costs, emissions and resource use.

Table C.1 presents the key values representative of the simulated scenario.

Emissions	
Construction phase	5 882 kt CO_2eq
Operation phase	12 655 kt CO_2eq
Total GWP	18 538 kt CO_2eq
Cost	
Investment (C_{inv})	37 984 M€
Maintenance (C_{maint})	17 523 M€
Operation (C_{op})	24 492 M€
Total system cost (C_{tot})	80 000 M€
System Characteristics	
Imported energy share	58 %
Storage utilization	48 TW h

Electrification Rates	
High temperature heat	56 %
Low temperature heat	100 %
Public mobility	19 %
Private mobility	0 %
Freight mobility	3 %
Storage	2 %

Table C.1: Key indicators of the **Min gwp corrected** scenario in 2050. Cost and emission values are expressed on an annual basis for the year 2050. The electrification rate of storage refers to technologies operating exclusively with electricity as input.

Figure C.1 shows the construction and operational emissions associated with the **min gwp corrected** scenario.

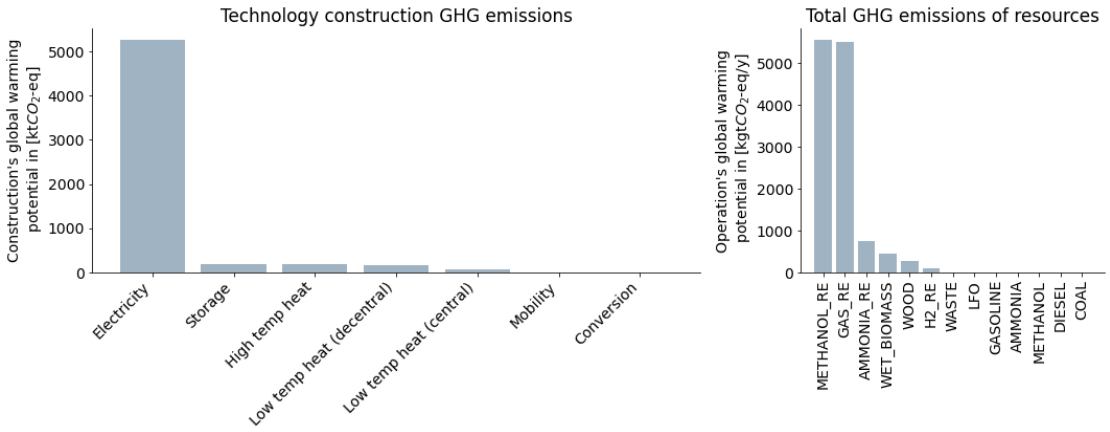


Figure C.1: Greenhouse gas emissions: construction and operation (a) Cumulative GHG emissions from technology construction, by category, expressed in kt CO_2eq. (b) Annual GHG emissions from resource use (operational phase), by energy carrier. Electricity production accounts for a very large share of emissions and methanol is present as a buffer.

Figure C.2 shows the investment, maintenance and operating costs associated with the **min gwp corrected** scenario.

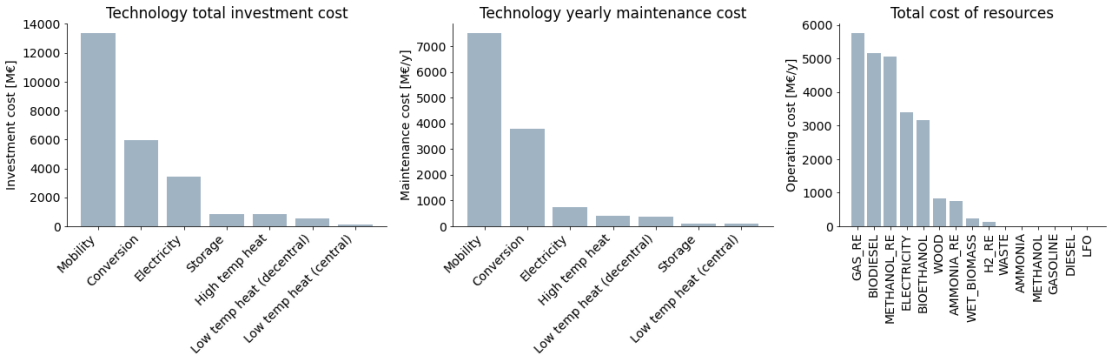


Figure C.2: Total investment, maintenance and operating costs (a) Total cumulative investment costs by technology category, (b) annual maintenance costs and (c) annual operating costs by energy resource. Values are expressed in million euros. Mobility consistently accounts for the largest investments.

Figure C.3shows the resources used in the simulated scenario.

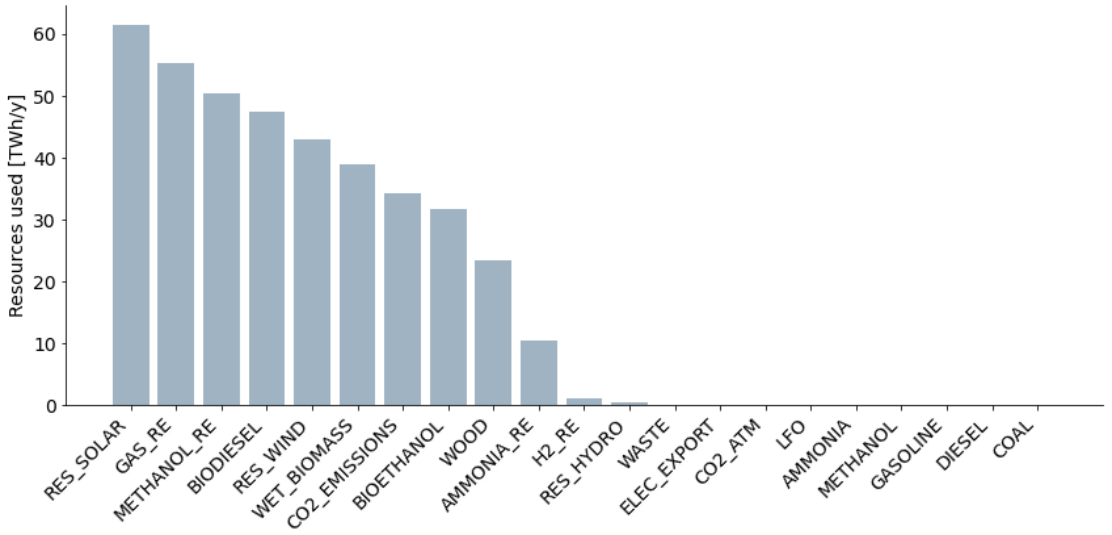


Figure C.3: Total quantities of resources used in 2050, expressed in $\mathrm{TW\,h\,y^{-1}}$. Energy carriers are ranked in descending order of consumption. The dominant resource used has once again become local.

Figure C.4 shows the installed capacity for electricity generation, low-temperature heat and high-temperature heat in the simulated scenario.

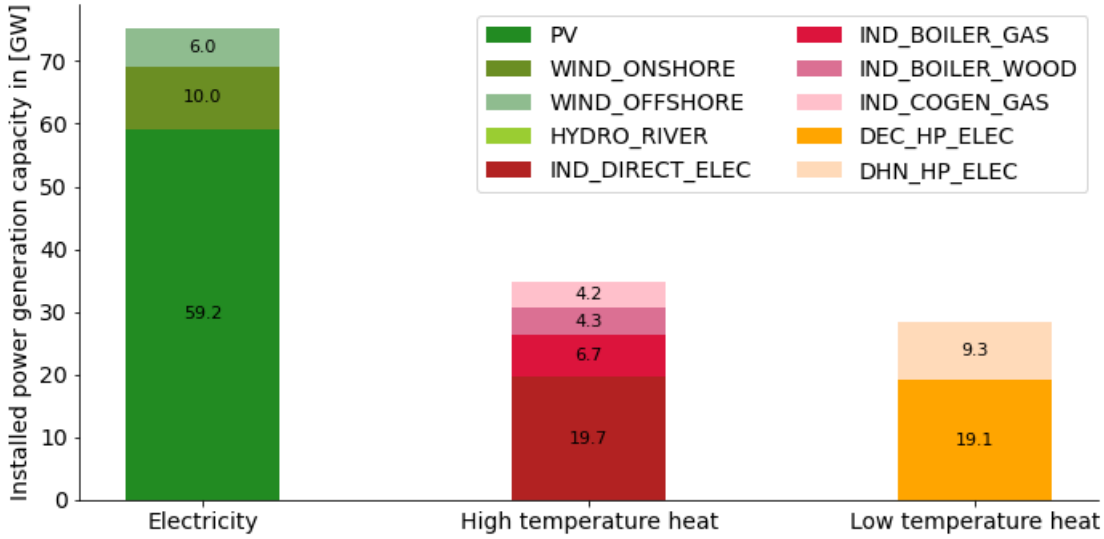


Figure C.4: Installed capacities in 2050 for electricity, high-temperature heat and low-temperature heat production sectors. Values are expressed in GW and represent the optimal capacity determined by the model for each dominant technology. In each sector, a re-electrification trend is observed.

Figure C.5 shows the installed capacity in the private and public mobility and freight transport sectors.

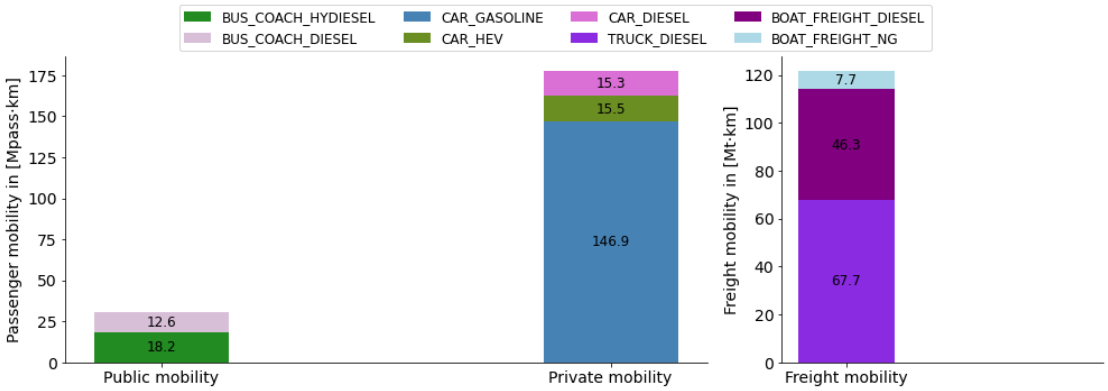


Figure C.5: Distribution of installed capacities for public and private mobility in Mpkm and freight mobility in Mt km in 2050. Many technologies rely on diesel.

Figure C.6 shows installed storage capacity by category: electrical, thermal and biofuels.

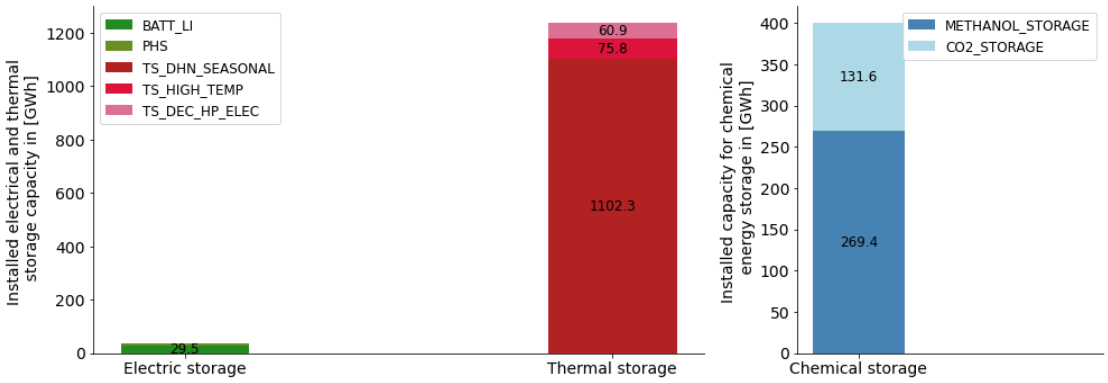


Figure C.6: Optimal installed capacities in 2050 for electrical and thermal storage and for chemical energy carrier storage. Technologies are grouped by storage type. The mix is similar to the reference scenario, with the emergence of methanol.

C.2 Stochastic analysis of storage technologies

This section presents the results of the stochastic sensitivity analysis focusing on the GWP_{constr} of storage technologies. The objective is to identify how uncertainty on these parameters influences key system-level outcomes such as installed capacities, energy carrier choices and mobility-related infrastructure. Correlations are computed across the ensemble of simulations performed using the RHEIA surrogate model.

The following figures show the significant box plots for the **min gwp corrected** scenario. Figure C.7 shows the variations in installed capacity in biofuels storage.

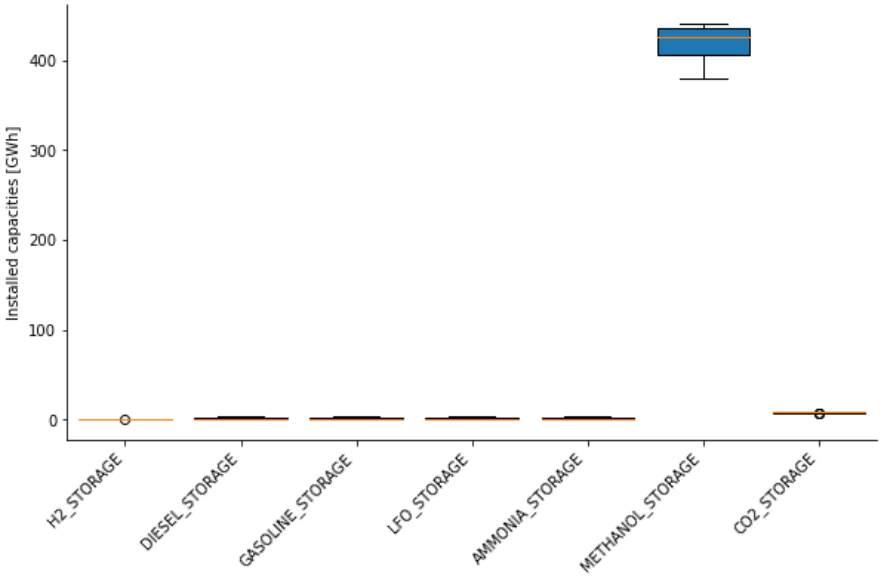


Figure C.7: Chemical and liquid energy storages
Boxplot of the installed capacities (GW h) for different chemical and liquid energy storage technologies.

Figure C.8 shows the variations in installed capacity in seasonal storage.

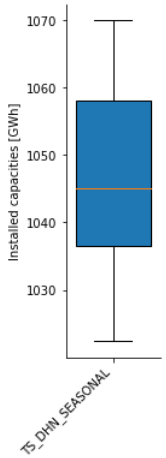


Figure C.8: Seasonal thermal storage
Boxplot of the optimal installed capacities (GW h) for seasonal thermal storage across all simulations.

Figure C.9 shows the variations in installed capacity in thermal storage.

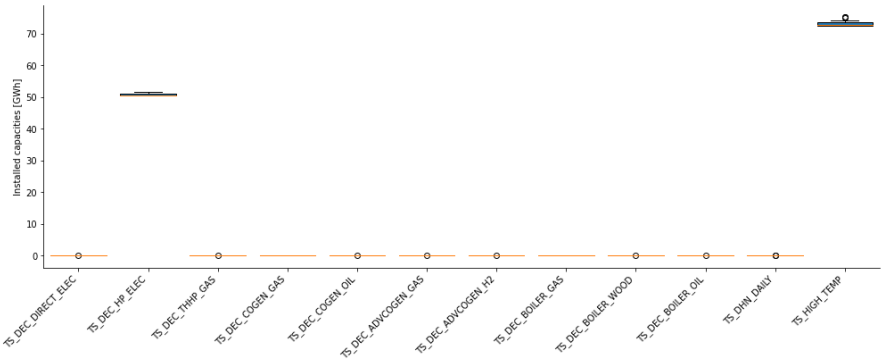


Figure C.9: Decentralised thermal storages and district heating network Boxplot of the installed capacities (GW h) for decentralised thermal storage technologies and district heating network options.

Figure C.10 examines how the $\mathrm{GWP}_{\mathrm{constr}}$ of each storage technology influences its own deployment within the energy system.

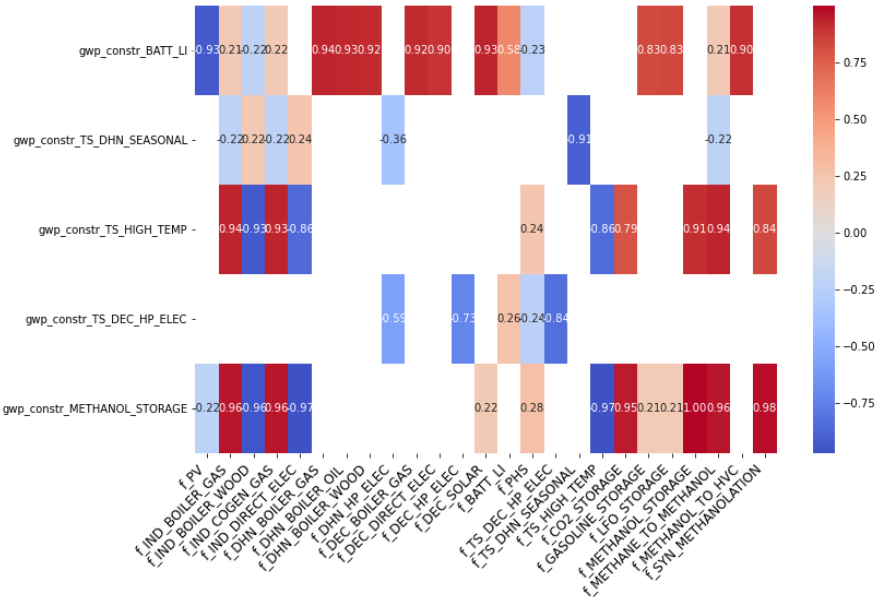


Figure C.10: Correlation between the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies and their installed capacity. Each bar shows how a change in the GWP of a given technology influences its presence in the optimized system across the stochastic design space.

The Figure C.11 explores the indirect effects of varying storage GWP on the mobility sector, reflecting how constrained storage options can shift technological choices in transport.

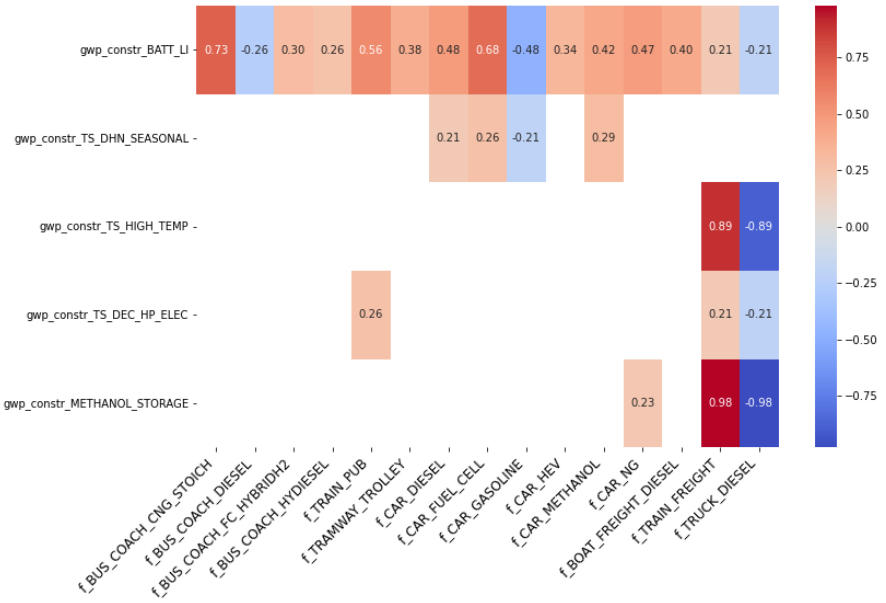


Figure C.11: Correlation between the $\mathrm{GWP}_{\mathrm{constr}}$ of storage technologies and the installed capacities of mobility technologies. These results highlight cross-sectoral interactions between storage and transport system choices.

Finally, the Figure C.12 highlights how storage-related environmental constraints affect the selection of energy carriers, providing insight into system-level reallocations.

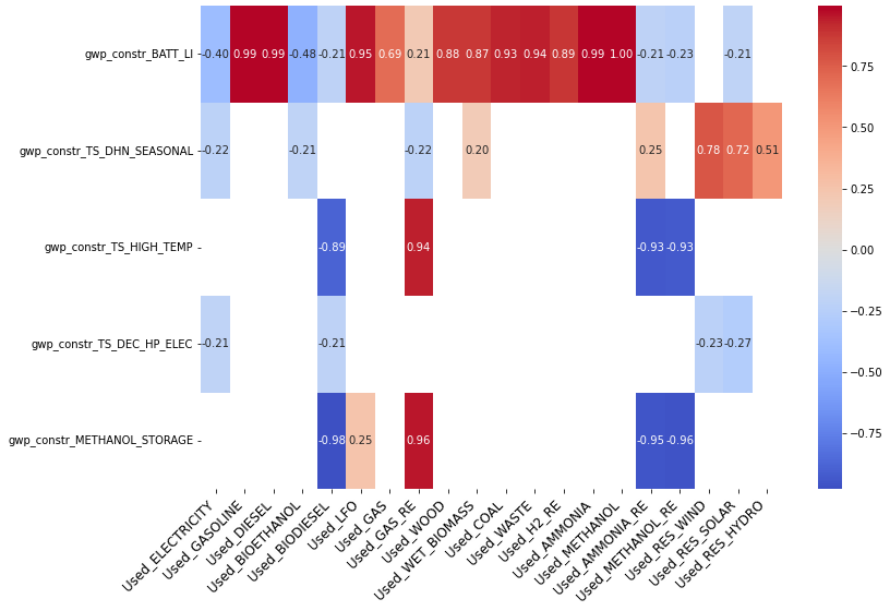


Figure C.12: Correlations between the GWP_{constr} of storage technologies and the resources used

Appendix D

Tipping points and interactions of storage technologies

This appendix presents detailed graphical results related to the behavior of storage technologies under increasing environmental constraints. It includes tipping point curves, systemic transition thresholds and co-variation patterns, providing a complementary view to the analyses discussed in Section Section 3.5.

D.1 Installed capacity transitions under increasing GWP

This section presents the evolution of installed capacities for different storage technologies under increasing values of GWP_{constr}. By progressively raising the environmental burden associated with the construction of a given technology, the system optimizes its configuration, potentially triggering the appearance, substitution, or disappearance of storage options. These curves provide insight into the resilience and flexibility of the technologies considered and help identify key thresholds of emergence, tipping and phase-out.

D.1.1 Technologies already present in the system

These figures show the behaviour of technologies that are already widely present in the mix. Their evolution is observed as their GWP_{constr} increases, revealing various transition patterns and substitution dynamics with other storage solutions.

The Figure D.1 focuses on the effects caused by varying the GWP_{constr} of lithium-ion batteries.

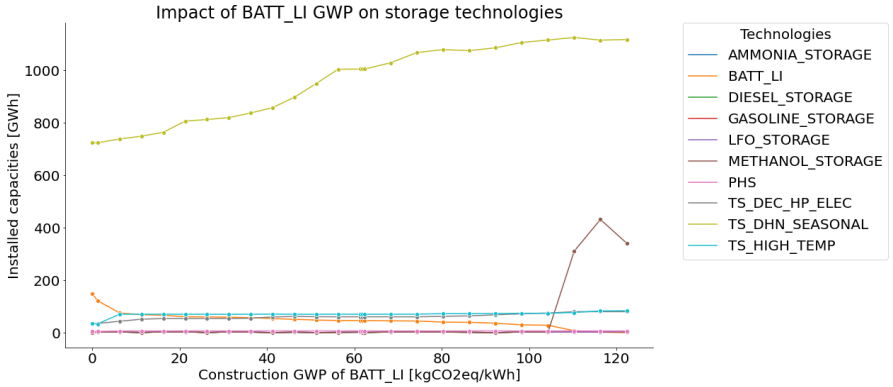


Figure D.1: Evolution of installed capacities for Li-ion batteries and other storage technologies under increasing $\text{GWP}_{\text{constr}}$ for Li-ion battery.

The Figure D.2 focuses on the effects caused by varying the $\text{GWP}_{\text{constr}}$ of high-temperature heat storage.

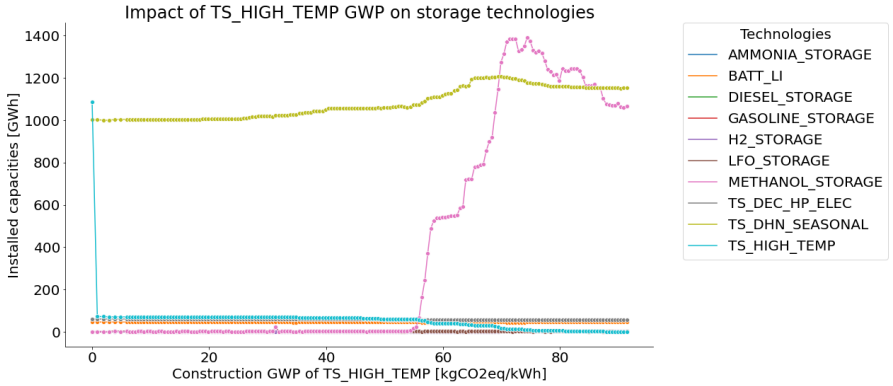


Figure D.2: Installed capacity trends for high temperature thermal storage, showing substitution patterns as its $\text{GWP}_{\text{constr}}$ increases.

The Figure D.3 focuses on the effects caused by varying the $\text{GWP}_{\text{constr}}$ of high-temperature heat storage.

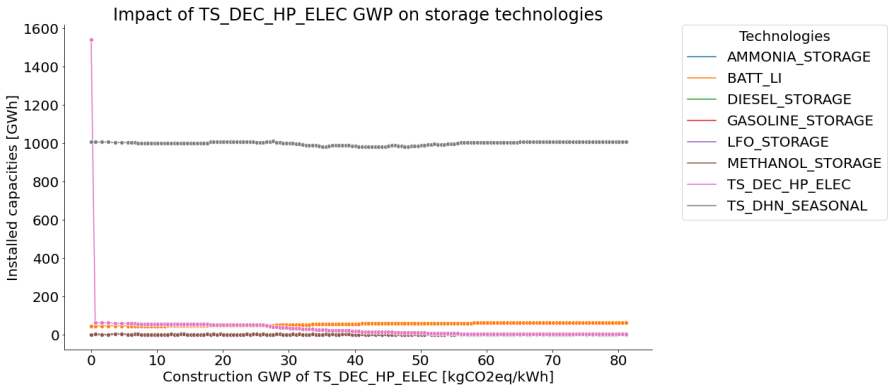


Figure D.3: Capacity evolution of decentralised low-temperature storage using an electric heat pump, showing partial resilience followed by substitution depending on GWP thresholds.

The Figure D.4 focuses on the effects caused by varying the $\mathrm{GWP}_{\mathrm{constr}}$ of PHS.

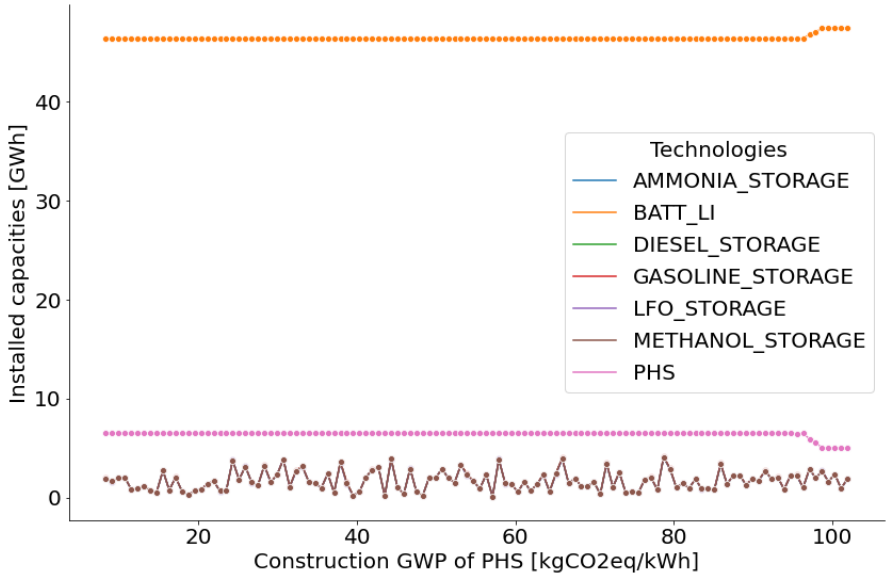


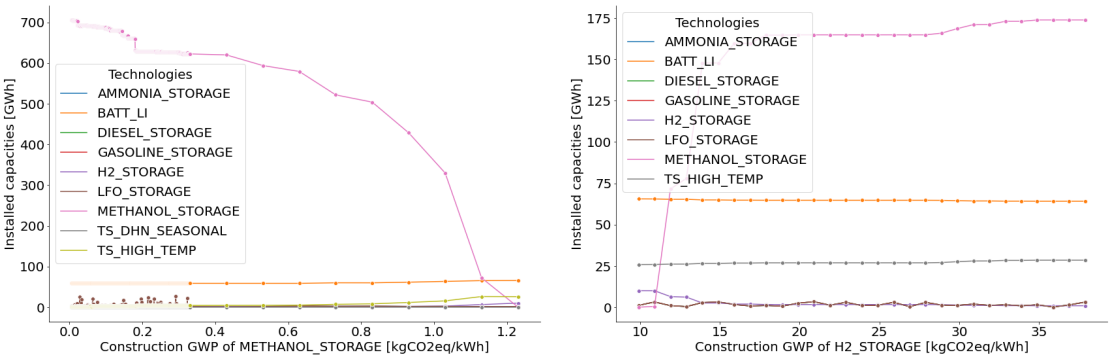
Figure D.4: Installed capacities of PHS and co-evolving technologies under rising $\mathrm{GWP}_{\mathrm{constr}}$ for PHS.

D.1.2 Technologies emerging through cascading effects

Some storage technologies are not selected in the reference scenario but become part of the optimal system when other dominant options become environmentally

penalized. These figures illustrate such cascading appearances.

Figure D.5 focuses on the effects caused by increasing the GWP_{constr} of several cascading modified technologies. In order, the modified technologies are seasonal storage, methanol storage and hydrogen storage before returning to the known dominant technologies.



(a) Progressive introduction of methanol storage as other options become less favourable.

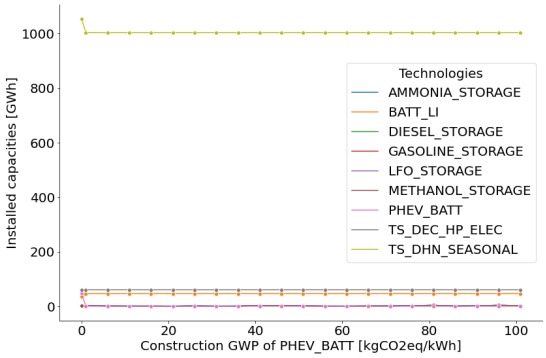
(b) Emergence of hydrogen storage due to penalization of competing technologies.

Figure D.5: Technologies appearing in the mix through cascading substitution when other storage solutions face higher GWP_{constr}.

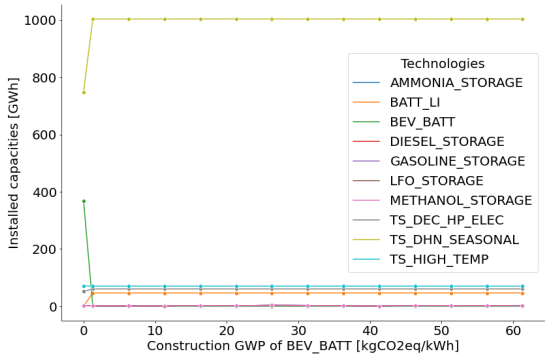
D.1.3 Technologies absent or marginal in the reference system

The following technologies were either absent or present in negligible quantities under the reference scenario. Their curves highlight under what environmental constraints they may become relevant in the system.

Figure D.6 shows the impact of the decrease in the GWP_{constr} of electric storage technology construction on other storage technologies. Figure D.6a shows the case of the PHEV battery and Figure D.6b shows the case of the BEV battery.



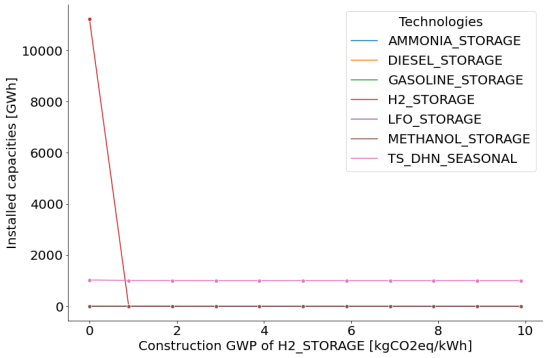
(a) Behaviour of the PHEV battery and developments in other storage technologies as its GWP_{constr} increases



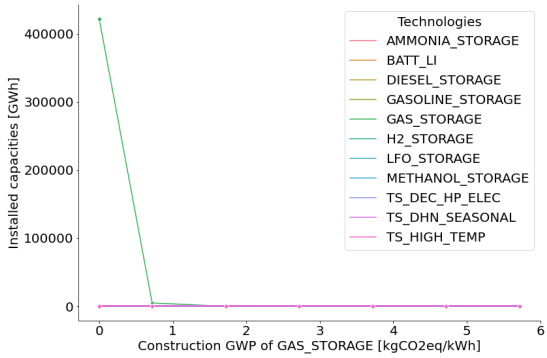
(b) Behaviour of the BEV battery and developments in other storage technologies as its GWP_{constr} increases

Figure D.6: Electrical storage technologies whose installed capacity only increases under specific environmental pressures.

Figure D.7 shows the impact of decreasing storage GWP_{constr} on biofuels themselves and on other storage technologies. Figure D.7a shows the case of the hydrogen storage and Figure D.7b shows the case of the gas storage.



(a) Reduction in the GWP_{constr} of hydrogen storage and the appearance of installed capacity when the GWP_{constr} is zero.



(b) Reduction in the GWP_{constr} of gas storage and emergence of installed capacity.

Figure D.7: Technologies with low initial deployment that appear when their GWP_{constr} decreases.

D.2 Share of scenarios showing systemic transitions

This section presents detailed results of the observed co-variations between energy storage technologies. Each figure illustrates the impact of the installed capacity

variation of a trigger technology via its GWP_{constr} on the installed capacity shares of other technologies.

The figures are derived from the methodology described in Section 2.5.

The horizontal bars indicate the proportion of scenarios in which a technology's capacity increases, decreases, or remains stable. These results allow for the identification of substitution, complementarity, or independence relationships between technologies, as well as an assessment of their systemic flexibility.

Some technologies, such as battery-powered BEV and PHEV, appear in only a very limited number of scenarios. Their results are therefore not presented, as they are considered non-representative.

D.2.1 Electric storage

Figure D.8 shows the impact of PHS variation on other storage technologies.

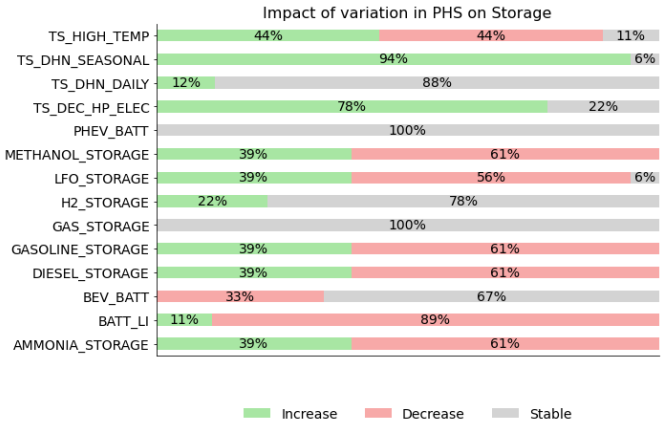


Figure D.8: Impact of the installed capacity variation of PHS on other storage technologies. A positive influence is notably observed on seasonal thermal storage and decentralized heat pump storage. Daily thermal storage and gas storage do not show any significant response. Lithium-ion battery storage is negatively affected.

Figure D.9 shows the impact of Li-ion batteries variation on other storage technologies.

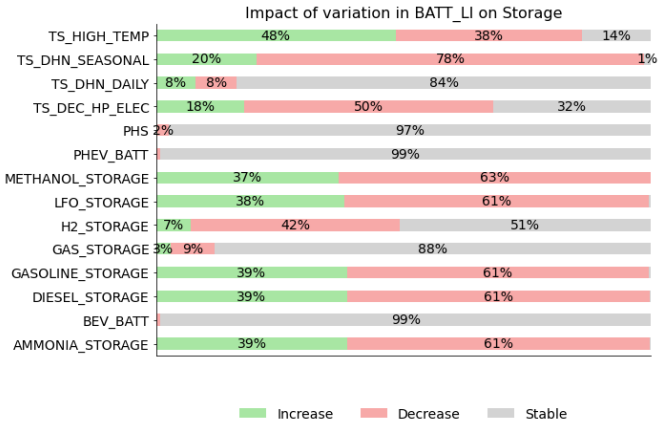


Figure D.9: Impact of the variation in installed capacity of Li-ion battery storage on other technologies. A decline in seasonal thermal storage is observed, while PHS remains largely unaffected.

D.2.2 Thermal storage

Figure D.10 shows the impact of centralized daily thermal storage variation on other storage technologies.

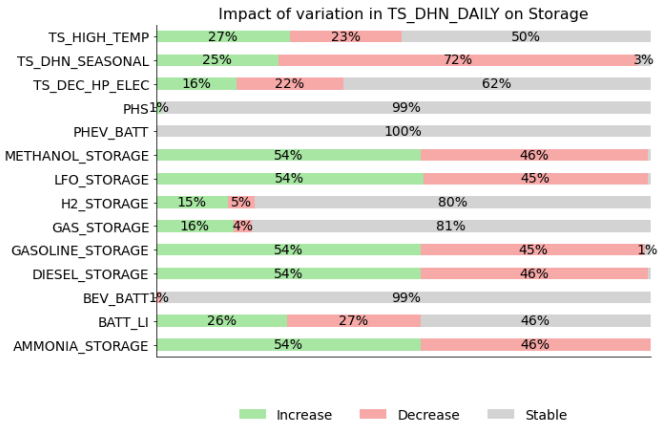


Figure D.10: Impact of the installed capacity variation of centralized daily thermal storage on other technologies. A notable reduction in seasonal storage is frequently observed. Biofuel-based storages exhibit heterogeneous responses, while hydrogen and gas storage remain mostly stable.

Figure D.11 shows the impact of storage integrated in decentralized electric heat pumps.

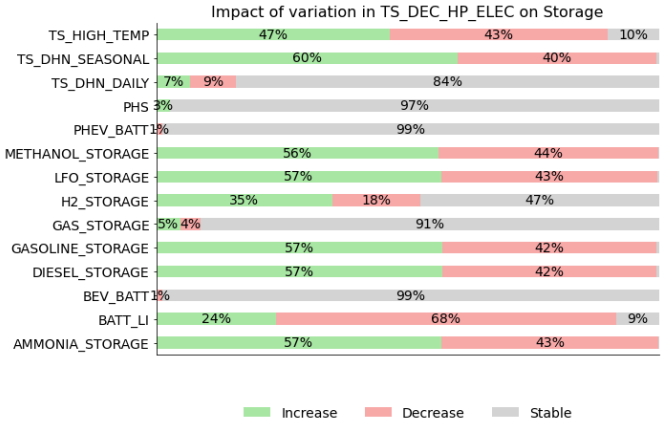


Figure D.11: Impact of the installed capacity variation of decentralized electric heat pump storage on other storage technologies. Lithium-ion battery storage is negatively affected in most cases. Biofuel storage technologies show contrasting behaviours.

Figure D.12 analyses the impact of seasonal thermal storage on other storage options.

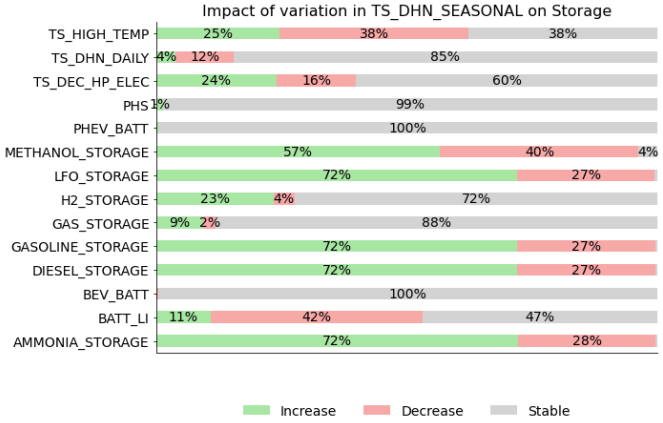


Figure D.12: Impact of the installed capacity variation of seasonal thermal storage on other technologies. An increase in biofuel storage is observed. Little impact is noted on daily, hydrogen, or gas storage.

Figure D.13 analyses the impact of high-temperature heat storage on other storage options.

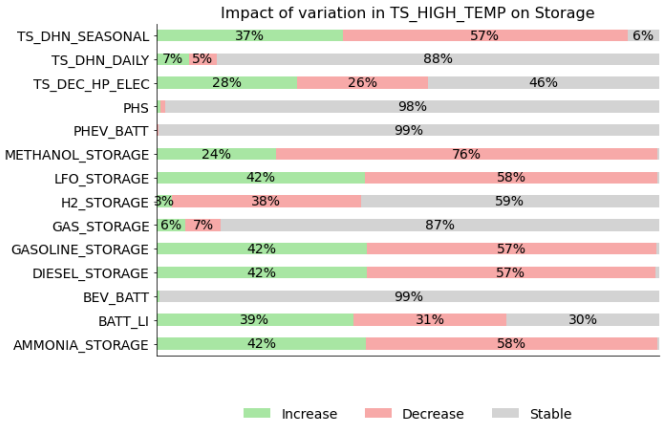


Figure D.13: Impact of the variation in installed capacity of high-temperature heat storage on other storage technologies. A strong negative influence is observed on methanol-based storage.

D.2.3 Biofuel storage

Figure D.14 presents the impact of gas storage.

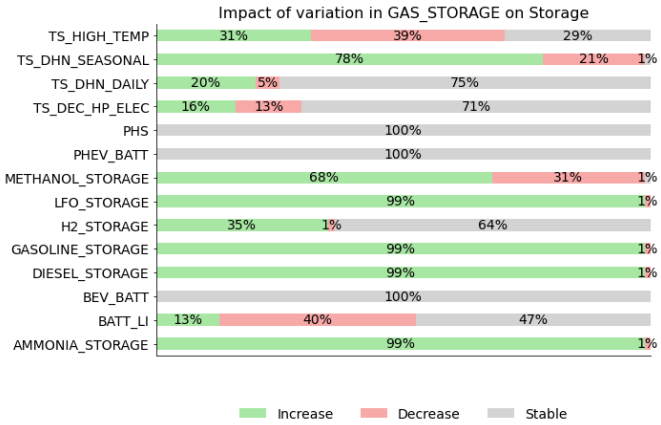


Figure D.14: Impact of the installed capacity variation of gas storage on other storage technologies. Biofuel storage is clearly favoured, as is seasonal thermal storage. Lithium-ion battery storage and high-temperature storage exhibit mixed effects depending on the scenario.

Figure D.15 presents the impact of hydrogen storage.

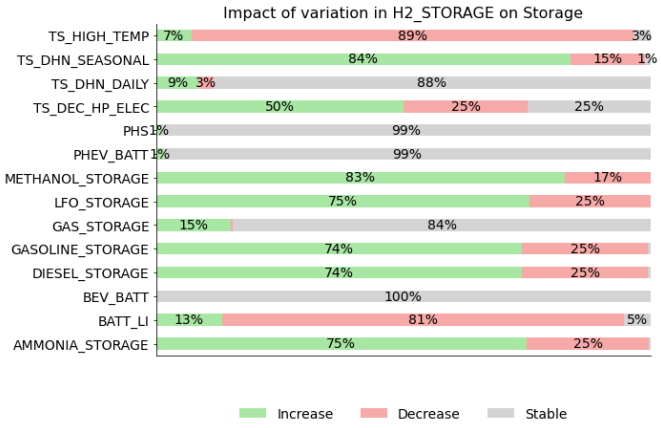


Figure D.15: Impact of the installed capacity variation of hydrogen storage on other technologies. Biofuel storage and seasonal storage benefit from the variation. High-temperature storage and lithium-ion batteries are generally penalized. Daily thermal storage remains stable in most cases.

Figure D.16 shows the effects of methanol storage.

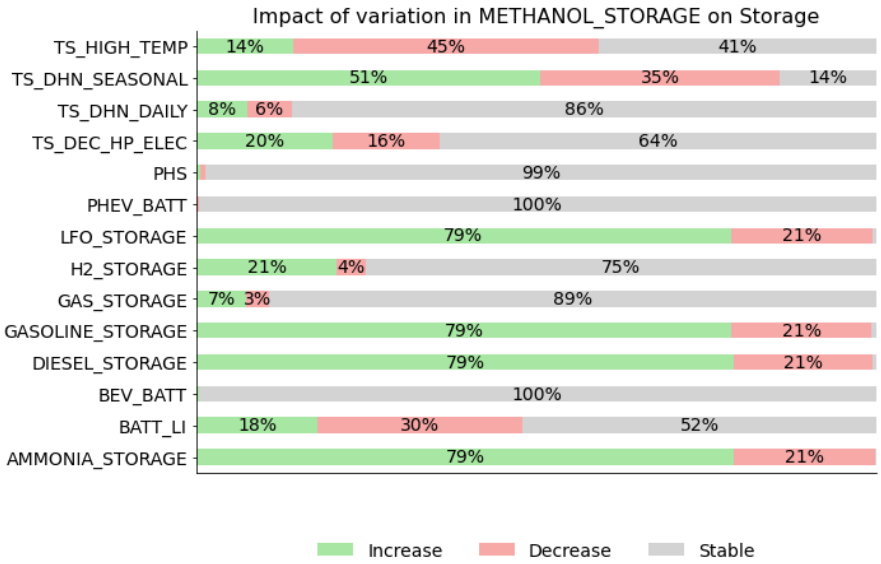


Figure D.16: Impact of the installed capacity variation of methanol storage on other technologies. Other biofuel storages are mostly favoured, except hydrogen and gas storage which remain largely stable.

D.3 Effects of storage GWP on other storage technologies

This section reports how the variation of GWP_{constr} of a given storage technology influences the capacity of other storage options. The graphs illustrate relationships of substitution, complementarity, or independence between technologies. The data revealed significant changes only in the freight transport sector.

Figure D.17 shows the influence of the increase in the GWP_{constr} of the Li-ion battery on technologies in the freight transport sector.

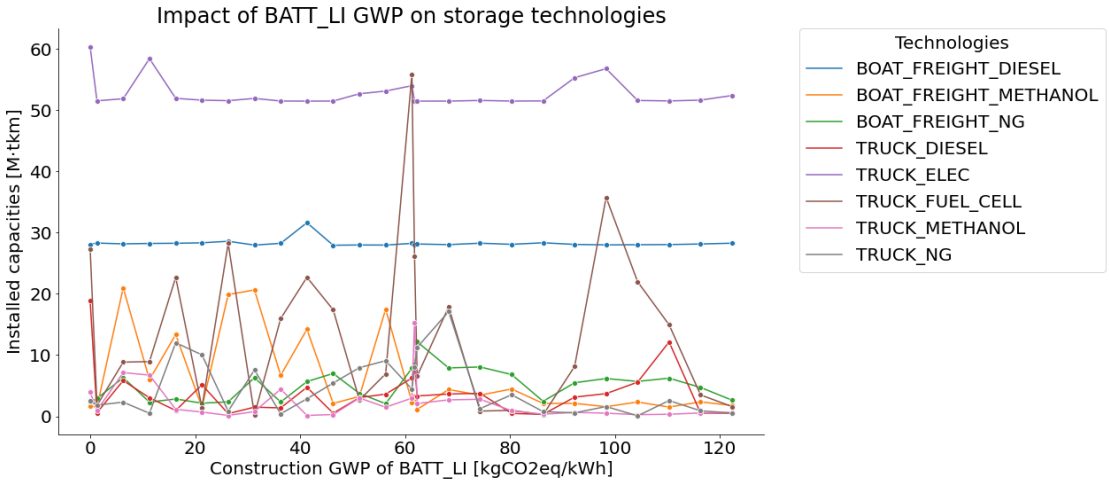


Figure D.17: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of the Li-ion battery.

Figure D.18 shows the influence of the increase in the GWP_{constr} of the BEV battery on technologies in the freight transport sector.

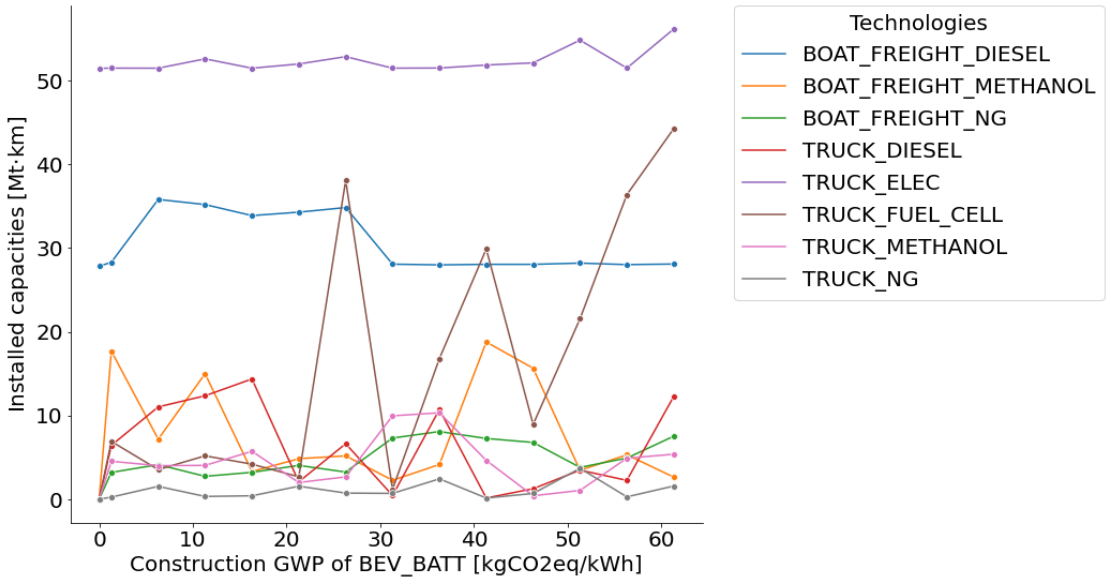


Figure D.18: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of the BEV battery.

Figure D.19 shows the influence of the increase in the GWP_{constr} of the high temperature heat storage on technologies in the freight transport sector.

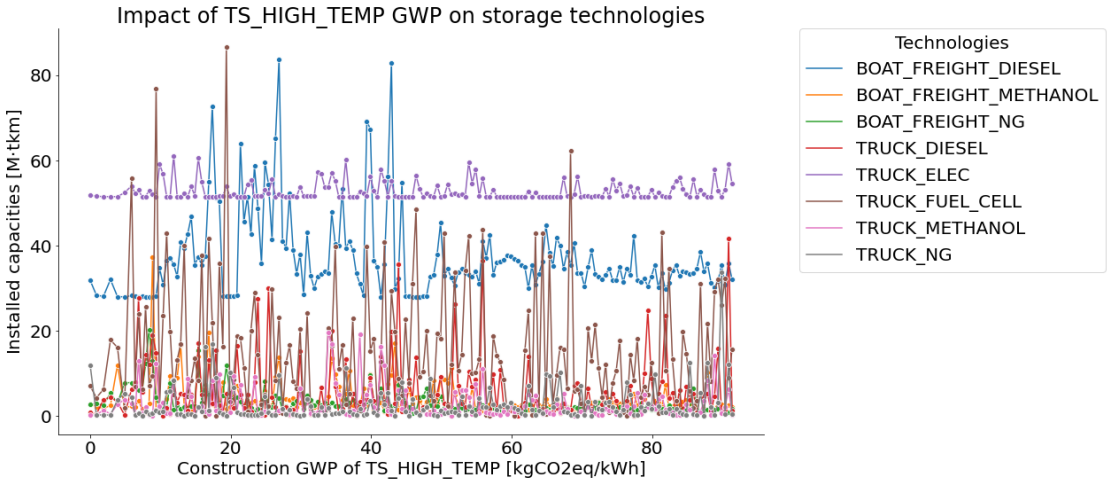


Figure D.19: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of the high temperature heat storage.

Figure D.20 shows the influence of the increase in the GWP_{constr} of storage integrated in decentralized electric heat pumps on technologies in the freight transport sector.

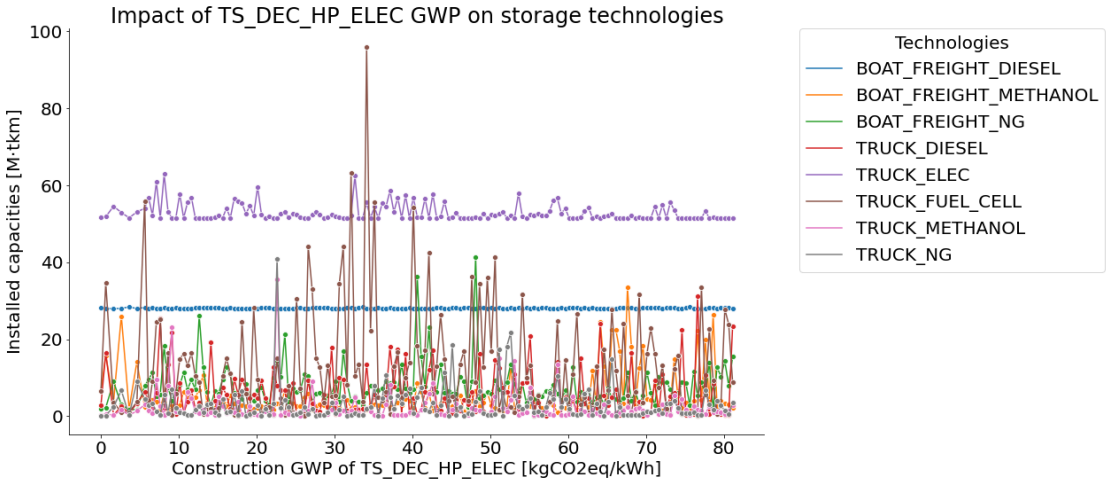


Figure D.20: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of storage integrated in decentralized electric heat pumps on technologies.

Figure D.21 shows the influence of the increase in the GWP_{constr} of PHEV battery on technologies in the freight transport sector.

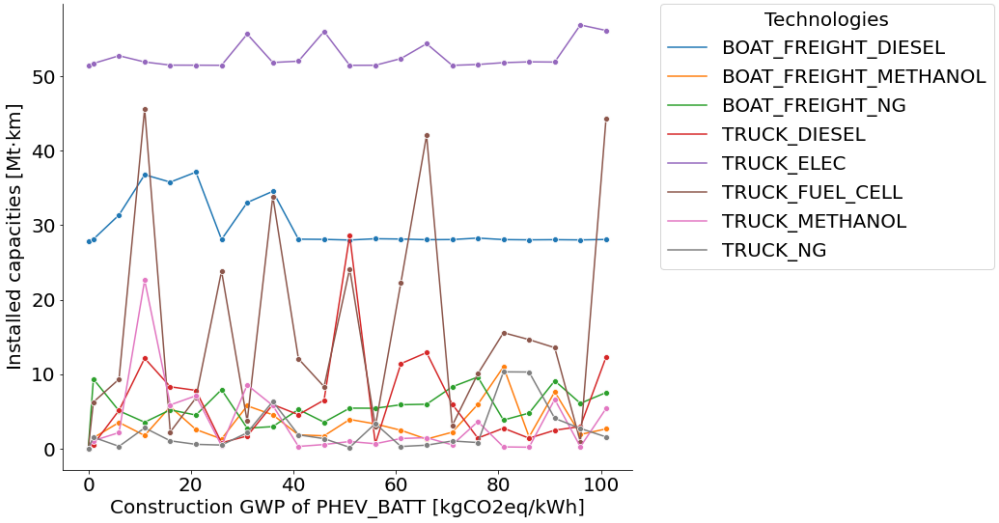


Figure D.21: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of PHEV batterie.

Figure D.22 shows the influence of the increase in the GWP_{constr} of PHS on technologies in the freight transport sector.

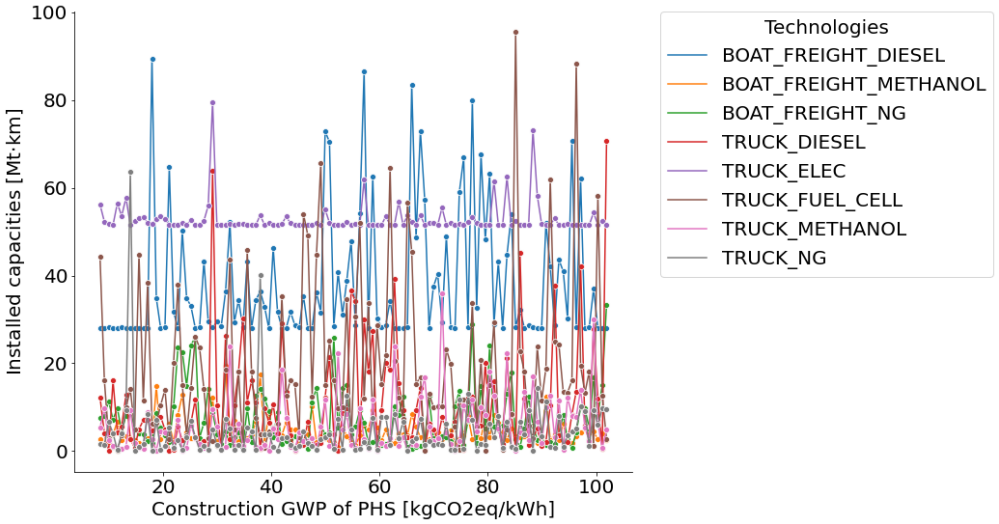


Figure D.22: Variation in technologies in the freight transport sector following the increase in the GWP_{constr} of PHS.

Appendix E

Stochastic analysis on private mobility

This appendix compiles the most relevant figures from the stochastic analysis conducted on private mobility. The analysis focuses on the GWP_{constr} values of private mobility technologies, as documented in the reference data of EnergyScope TD[43]. Following the recommendations of Moret [54], each uncertain parameter was subjected to a relative variation of 20 %. In the absence of more precise information to justify a specific probability law, a uniform distribution was applied to all parameters, as stated by Rixhon [68].

Data not shown in the boxplots correspond to technologies whose installed capacity remained either null or constant across all simulations. All datasets used for this analysis are available in the official GitHub repository, as detailed in Appendix F.

Figure E.1 presents the distribution of installed capacities for private mobility technologies.

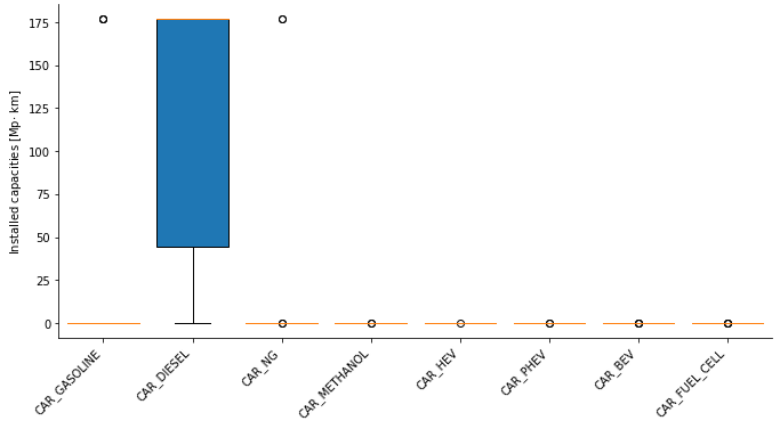


Figure E.1: Distribution of installed capacities for private mobility (Mt · km) by vehicle technology. This representation illustrates the prevalence and variability of certain powertrains, particularly diesel. Variations in diesel car are occasionally compensated by increases in NG car and gasoline car.

Figure E.2 illustrates the distribution of installed freight transport capacities by energy carrier.

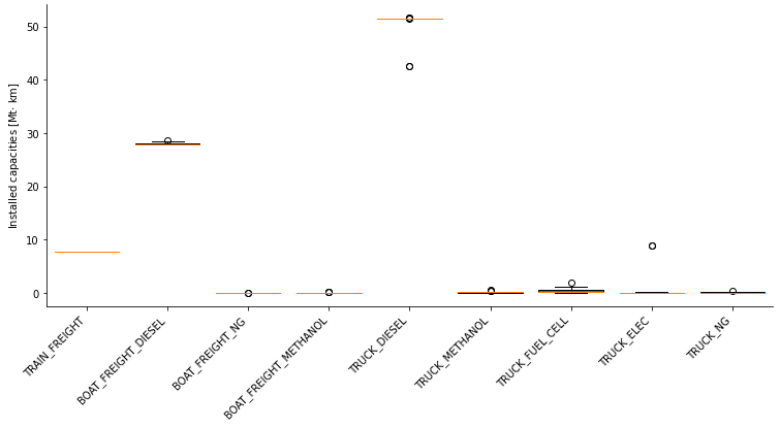


Figure E.2: Distribution of installed capacities for freight transport (Mt · km) by energy carrier. The results highlight dominant technologies and their sensitivity to variations in uncertain parameters. The capacity of FCET shows notable variability.

Figure E.3 shows the distribution of installed storage capacities for different energy carriers.

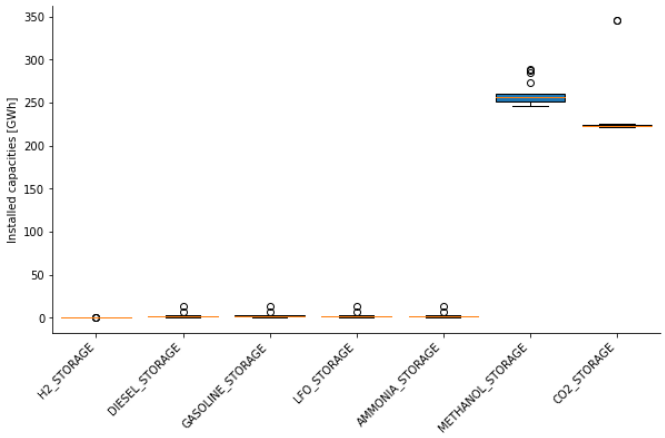


Figure E.3: Distribution of installed storage capacities (GWh) for different energy carriers. The boxplots show the variability arising from the uncertainty applied to input parameters, with outliers represented by points. Methanol storage is the only storage technology showing noticeable variability across simulations.

Figure E.4 presents the correlation matrix between the $\text{GWP}_{\text{constr}}$ of mobility technologies and the installed capacities of storage and mobility technologies.

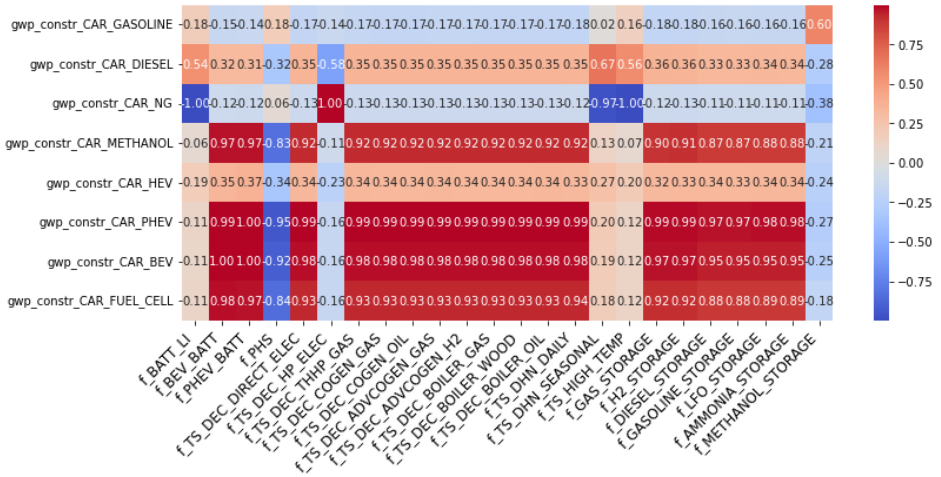


Figure E.4: Correlations between the $\text{GWP}_{\text{constr}}$ of mobility technologies and the installed capacities of storage and mobility technologies. Coefficients are calculated from stochastic simulations and reflect the direction and strength of relationships between variables. The strong positive correlation of 0.6 between methanol storage and $\text{GWP}_{\text{constr}}$ car gasoline is particularly noteworthy.

Appendix F

GitHub repository content

The GitHub repository created for this work contains all the materials required to reproduce the analyses presented in this thesis. It is organised into several directories, each corresponding to a specific type of content:

- `energyscope`: Contains the customised version of EnergyScope TD used in this work, including all model adaptations, additional constraints and data modifications implemented for the analyses. The main modifications include: the addition of GWP_{op} values for biofuels in `Resources.csv`; the addition of GWP_{constr} values for storage technologies; the change of the optimisation objective from total cost to total GWP; the change in GWP consideration from GWP_{op} to total GWP; and the addition of a price constraint.
- `rheia`: Contains the version of RHEIA used for the stochastic analyses, along with the configuration parameters applied. The main changes compared to the standard EnergyScope TD case include: a complete redesign of the `design_space` and `stochastic_space` definitions, as well as the change of the optimisation objective from total cost to total GWP.
- `csv_data`: Contains all `.csv` files generated from EnergyScope TD outputs, organised by scenario and data type. These files mainly correspond to the datasets produced during the tipping point identification analyses.
- `scripts_analysis`: Contains the Python scripts used for processing and analysing the raw results, including indicator calculation and data aggregation.
- `scripts_plots`: Contains the Python scripts used for generating the graphs, figures and visualisations presented in this master thesis and appendices.

The repository is accessible at: `https://github.com/leareyntjens/Code_TFE.git`.

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