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EnergyScope Pathway: a model to optimize Italy's energy transition

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To my beloved parents, and to all those who made Padova feel like a second home to me.

Thank you, grazie, gracias, hvala, danke, مرسی*, teşekkürler,* ధన్యవాదాలు*. Moltes gràcies a tots.*

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Sommario

Data l’urgenza della crisi climatica, la transizione energetica dell’Italia richiede strumenti solidi per analizzare e guidare l’evoluzione del sistema. Molti modelli esistenti simulano scenari a lungo termine, ma spesso trascurano il dettaglio dei percorsi e le dinamiche orarie necessarie per integrare efficacemente le fonti rinnovabili intermittenti. Questo lavoro utilizza EnergyScope Pathway, un modello open-source che ottimizza sia le decisioni di investimento a lungo termine sia il funzionamento orario dell’intero sistema energetico. Applicato al contesto italiano, il modello aiuta a identificare strategie coerenti basate su efficienza energetica, elettrificazione e integrazione delle rinnovabili. L’obiettivo non è proporre un nuovo metodo, ma dimostrare come un framework di modellizzazione trasparente e adattabile possa supportare l’analisi delle transizioni energetiche nazionali con maggiore chiarezza e riproducibilità.

Abstract

Given the urgency of the climate crisis, Italy’s energy transition requires robust tools to analyze and guide system evolution. Many existing models simulate long-term scenarios but often overlook the detailed Pathway and hourly dynamics needed to integrate intermittent renewables effectively. In this work EnergyScope Pathway for Italy is developed, an open-source model that optimizes both long-term investment decisions and hourly operation across the entire energy system. Applied to the Italian context, the model helps identify consistent strategies based on energy efficiency, electrification, and renewable integration. The aim is not to propose a new method, but to demonstrate how a transparent and adaptable modelling framework can support the analysis of national energy transitions with greater clarity and reproducibility.

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1. Introduction

The intensifying impacts of climate change have catalyzed a global consensus on the urgency of transitioning towards a carbon-neutral society. Greenhouse gas (GHG) emissions have been the primary driver of global warming, with the energy system being the dominant contributor, accounting for approximately 73% of global GHG emissions as of 2019 [1]. The scientific community, through successive reports from the Intergovernmental Panel on Climate Change (IPCC), has warned that limiting global temperature rise to 1.5 °C above pre-industrial levels requires global net-zero CO_2 emissions by around mid-century [2]. Failing to meet this objective would exacerbate the frequency and intensity of extreme weather events, threaten ecosystems, and undermine human development across the globe [3].

In response to this challenge, international efforts have been made around a series of legally binding and voluntary frameworks. Most notably, the Paris Agreement, agreed in 2015 under the United Nations Framework Convention on Climate Change (UNFCCC), obliges signatory nations to pursue efforts to limit global warming to well below 2 °C, and preferably to 1.5 °C [4]. Meeting this ambition means reducing global GHG emissions by about 45% from 1990 levels by 2030 and reaching net-zero around 2050 [2]. As part of this global effort, the European Union (EU) has committed to achieving climate neutrality by 2050 through the European Green Deal, a comprehensive roadmap adopted in 2019 [5]. The Green Deal mandates a reduction of net emissions by at least 55% by 2030 compared to 1990 levels, a goal operationalized through legislative packages such as Fit for 55 and REPowerEU, which accelerate the deployment of renewables, promote energy efficiency, and support the diversification of energy supply in response to geopolitical and climate risks [6], [7].

Italy, as a founding member of the EU and a signatory of the Paris Agreement, has added these commitments into national policy. The Integrated National Energy and Climate Plan (PNIEC) outlines Italy's targets for 2030, including a 33% reduction in GHG emissions in non-ETS sectors compared to 2005, a 30% share of renewables in gross final energy consumption, and a 43% improvement in energy efficiency [8]. In parallel, the Long-Term Strategy for Reducing Greenhouse Gas Emissions, published in 2021, confirms Italy's objective to achieve carbon neutrality by 2050 [9].

Despite notable progress, particularly in the electricity sector where renewables contributed around 37% of gross production in 2021 [10], Italy's energy system remains heavily dependent on fossil fuels. As of 2021, fossil fuels accounted for over 74% of total primary energy supply, with natural gas and oil dominating the residential, industrial, and transport sectors [10]. Moreover, Italy's high dependency on imported energy (around 74.5% in 2021 [10]) makes it vulnerable to price volatility and supply disruptions, as evidenced by the 2022 energy crisis triggered by geopolitical tensions. Achieving deep decarbonization therefore requires a comprehensive transformation of Italy's energy system, encompassing all sectors (electricity, heating and cooling, mobility, and industry) and leveraging a broad portfolio of technologies.

Key pillars of this transition include the large-scale deployment of renewable energy technologies (especially solar PV and wind), widespread electrification of end uses, the introduction of flexibility and storage solutions, and the coupling of sectors through power-to-gas, power-to-heat, and vehicle-to-grid schemes [11], [12]. However, due to the complexity and interdependence of these measures, long-term planning must be supported by rigorous and transparent energy system models. These models can simulate and optimize the evolution of national energy systems under varying assumptions, thereby helping policymakers, planners, and stakeholders identify technically feasible and economically viable pathways to net-zero.

Among the tools available, the EnergyScope model stands out for its balance between complexity, transparency, and computational efficiency. Developed at EPFL (École Polytechnique Fédérale de Lausanne), and later extended to national contexts such as Switzerland, Belgium and Italy, EnergyScope Pathway is an open-source, whole-energy system model that determines the optimal technology mix for a given year (typically 2050), under constraints on cost and emissions. Unlike many large-scale energy system models that rely on extensive temporal and spatial granularity, EnergyScope Pathway focuses on delivering a concise but robust representation of the energy system using hourly profiles for typical days, enabling fast computation and scenario exploration.

In addition to its simplified temporal resolution, EnergyScope Pathway introduces a critical intertemporal component: the model incorporates constraints that link investment and operational decisions across multiple representative years. This includes the automatic decommissioning of technologies once their lifetime expires, limitations on the annual rate of technology expansion (reflecting deployment inertia), and the optional early phase-out of existing assets before end-of-life. Moreover, it tracks cumulative investments and emissions over the entire time horizon, enabling the analysis of carbon budgets and policy compliance trajectories. These features provide a dynamic and policy-relevant representation of the energy transition, supporting decisions not only about the target end-state but also the pathway to reach it.

Previous literature exists about the EnergyScope methodology developed by Borasio and Moret [14]. Said study consists on snapshot version of EnergyScope (a previous approach) and has shown the potential of this methodology to explore alternative energy futures for the country. By integrating national energy balances, technology cost curves, renewable potentials, and hourly demand profiles, the model enables the identification of coherent decarbonization options consistent with climate neutrality. In addition, its open-source structure promotes transparency and reproducibility, fostering public trust and academic collaboration. However, this thesis aims to give it a different approach.

The objective of this thesis is to develop the new approach of EnergyScope to study energy transition on an energy system, EnergyScope Pathway. A new model adapted to the Italian energy system will be constructed, with the aim of identifying cost-optimal transition Pathway that enable full decarbonization by 2050. Special attention is given to the role of electrification, storage, and sectoral integration in achieving carbon neutrality, under different assumptions of policy ambition and technological availability (European Green Agreement, evolution of technologies, etc.). The analysis considers technical and economic parameters, renewable resource constraints, and hourly system dynamics to assess how Italy can meet its climate goals while ensuring energy security and, at the same time, minimizing the costs to achieve it.

In doing so, this work contributes to the growing literature on national energy transition modeling and provides decision-support insights for Italian energy policy. It also exemplifies the value of structured, transparent methodologies like EnergyScope Pathway in navigating the complex trade-offs and uncertainties inherent in long-term energy planning

2. State of the art

Energy systems are infrastructures that provide essential services like heating, transport, and electricity. While they can range from cellular to planetary scales, our concern is the global energy system that relies on fossil fuels and drives climate change.

The diversity of energy-related challenges has given rise to a wide array of models. Some support real-time operation of power plants, while others explore how to transition to low-carbon technologies. Each serves a specific function, requiring different assumptions and levels of detail.

This thesis focuses on a key question*: how does the Italian energy system have to evolve in other to achieve carbon neutrality by 2050? And, by doing so, how can we minimize economic and environmental impact?* To answer it, we need a model that meets four essential criteria, ensuring accurate and efficient storage in complex energy systems.

First, energy systems are becoming more interconnected. Future infrastructures will rely on strong integration across electricity, heating, and mobility. As Contino et al. note, such systems must be flexible, renewable, and sector coupled. Thus, the model should represent the entire energy system and capture inter-sector dynamics.

Second, climate planning demands transparency. Open, accessible models allow researchers to collaborate, share data, and replicate results — accelerating progress. Therefore, the model should be open-source, well-documented, and publicly available.

Third, the system's optimal design cannot be assumed. With increasing reliance on variable renewables, it is essential to explore how systems behave hour-by-hour throughout the year. Hence, the model should optimize both investments and hourly operation over an annual timeframe.

Finally, planning under uncertainty requires computational efficiency. To test many scenarios quickly, the model should run fast and scale well.

This chapter introduces a typology of energy models based on their function — operational control versus system design — and their level of detail. From this, we identify the class of models best suited to our research.

We then compare selected models against our four criteria, evaluating their system coverage, openness, optimization capabilities, and computational performance.

This analysis reveals gaps in existing tools. To address them, we present EnergyScope TD and its evolution (Pathway) as open-source models capable of supporting whole-system planning under uncertainty.

2.1 Types of energy system models

Energy system models differ significantly in how they address time and space, the depth of technical detail they incorporate, and the length of time they simulate. A widely accepted way to classify them is based on their main objective: either short-term system operation or long-term system planning.

Models developed for operational purposes are typically used to optimize the functioning of a specific sector—most often electricity—without considering infrastructure investment decisions. These tools offer high temporal resolution and are equipped to simulate quick shifts in renewable generation, manage forecast deviations, and assess grid balancing or reserve mechanisms. Their focus is on precise, real-time or near-term performance rather than structural evolution.

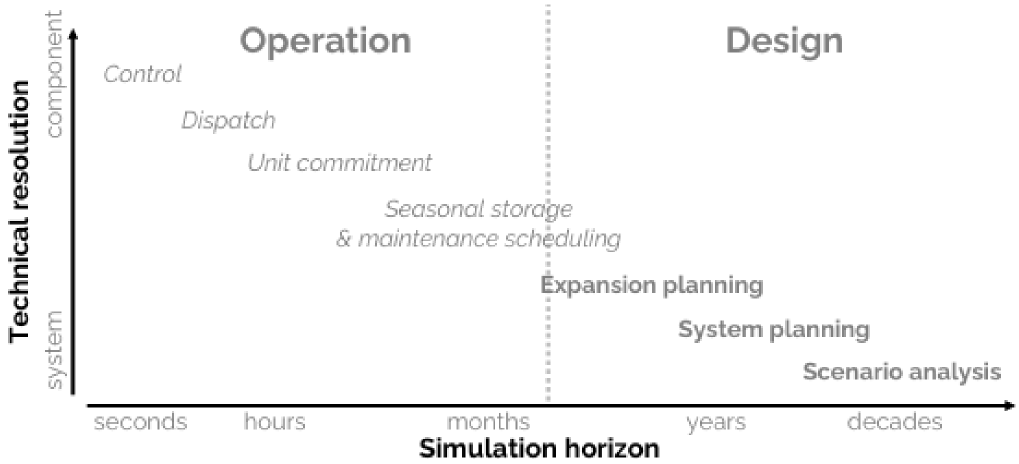

Figure 2.1 – Representation of different scopes of models

Conversely, planning models take a broader view. They are intended to evaluate how the energy system might develop over years or decades. These models do include investment choices—such as deploying new technologies or retiring existing capacity—and aim to design cost-effective or policy-aligned future systems. Their technical detail tends to be more abstract at the operational level but sufficient for long-range decision-making.

Since no single tool captures every dimension of an energy system, models within both categories are further broken down by their time horizon and resolution.

Within the operational category, models are tailored to different tasks. Control models work at sub-hourly scales and simulate the dynamic behavior of system components, incorporating failure risks. At slightly longer timeframes, dispatch models determine load allocation among generating units based on system conditions. Unit commitment models, on the scale of hours to days, help select which units to activate or shut down, usually using simplified operational parameters such as start-up costs. For monthly or seasonal decisions, models are used to coordinate storage levels and schedule maintenance to ensure adequate capacity.

When models address periods longer than a year, they shift away from operational concerns toward strategic questions. At the first level, expansion models analyze how existing infrastructure can be reinforced or extended. Beyond that, system planning models design the broader layout and evolution of the energy mix. Finally, in scenario analysis, the model is not constrained by the current system; it seeks to explore possible futures from scratch—testing the implications of different technological or policy assumptions.

Operational models are most appropriate for assessing immediate system stability and control. In contrast, planning models are better suited to evaluating long-term scenarios and policy impacts, especially for meeting decarbonization or sustainability goals. This work falls within the second group, with a particular focus on long-term system design and exploratory scenario modelling, which are discussed in depth later on.

2.2 Literature review

The field of energy system modelling is populated by a vast number of tools. For example, in his work in 2017 about energy system optimization models, DeCarolis et al. [15] identified up to 483 different ones. In such a landscape, it is fair to question the need for another model. Building upon prior work by Connolly et al. [16], Pfenninger et al. [17], Prina et al. [18], Moret et al. [19], and the Open Energy Modelling Initiative [20], a detailed review of 54 modelling tools was carried out. A selection of these is presented in Table 2.1.

Traditionally, most energy models have focused on a single sector, typically electricity, without accounting for sector coupling. For instance, EMMA [20] and SciGRID [22] are limited to the power system, a pattern shared by 18 of the reviewed models. Some tools, such as Dispa-SET [23], have evolved to partially incorporate heating and electric mobility. Among the remaining 36 models, 16 capture both electricity and heat, and another 16 include elements of the mobility sector. Still, most treat these linkages in a simplified way and do not represent a complete, interconnected energy system.

Accessibility also remains an issue: 14 of the models are not fully open access, such as STREAM [24], NEMS [26], and MARKAL/TIMES [25]. Additionally, 20 are not open source, including Plexos Open EU [27] and EnergyPLAN [28].

Beyond sector scope and transparency, a key methodological distinction lies between simulation and optimization. According to Wurbs [29], simulation involves predicting system behavior under predefined conditions, while optimization uses formal algorithms to find optimal solutions within constraints. Although optimization provides greater flexibility and is better suited for exploring future system configurations, it is more computationally demanding, which limits its use in uncertainty analysis [49]. Nevertheless, given the complexity of the energy transition and the number of unknowns involved, optimization is favored here—as is the case in 16 of the reviewed models.

Table 2.1 shows the subset of models that are freely available, offer monthly to hourly time resolution, and at least partially represent electricity, heating, and transport. Models are assessed against four criteria: (i) inclusion of all three sectors with sector coupling; (ii) open-source status; (iii) ability to optimize investments and hourly operations; and (iv) computational suitability for uncertainty applications. While additional aspects like spatial resolution or market dynamics could also be considered, the four selected criteria reflect the modelling needs of this work.

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

[a] The model focuses on the power system with the possibility to implement other sectors.
[b] Not suitable for uncertainty characterisation, yet [36] .
[c] Data missing
[d] Energy system includes partially heat and transport sectors.
[e] Operation is usually not resolved on a hourly base. For EnergyScope monthly, the operation are resolved over the twelve months.
[f] Energy system includes partially transport sector.

Table 2.1 – Comparison of different existing models

The results highlight that only eight models meet the requirements of being both open-source and optimization-based: DIETER [41], URBS [37], Switch [33], PyPSA [31], OSeMOSYS [30], Oemof [39], Calliope [36, 53], and both EnergyScope monthly and TD [46, 49]. However, each comes with limitations. The first four focus mainly on electricity, with only basic representations of heat and mobility. For instance, URBS includes electric vehicles but not broader transport modes. Switch also models EVs but lacks full transport sector integration. PyPSA provides detailed power system modelling, but other sectors are often simplified—as shown by Brown et al. [42], who model heat and mobility with only two technologies.

OSeMOSYS supports multi-year investment optimization but simplifies operations to representative time slices—often far from the 8760-hour resolution needed. Oemof and Calliope act more as modelling toolkits; despite active communities, no published studies at the time use them to model a complete multi-sector energy system. The EnergyScope monthly model satisfies most criteria but lacks hourly detail, solving operations at monthly intervals. This is appropriate for countries with low shares of intermittent renewables and limited short-term storage.

In conclusion, Table 2.1 illustrates that although existing models have specific strengths, none satisfy all four criteria simultaneously. These gaps justify the development or improvement of a modelling framework that is open, sector-integrated, computationally efficient, and capable of year-round, hourly-level optimization.

In the contest of EnergyScope the TD (typical days) version, also known as snapshot, further solves the limitations presented by its predecessor and achieves hourly resolution also simplifying the computation load implementing typical days, more about it in the following chapters. However, his approach is a quite static solution, in other words, you can not interact with the code during the optimization window, therefore a more dynamic approach is needed.

2.3 Energy models for system planning

The models discussed in the previous section are adequate for analyzing long-term configurations of energy systems, commonly referred to as scenario analysis. However, when the objective shifts to system planning, the modelling approach should include the dynamic evolution of the system from its current state to a future target—such as carbon neutrality by 2050. This implies that the model must not only optimize investment trajectories from today onward but also ensure that intermediate configurations remain technically feasible and operationally sound. As such, the required model is inherently more complex and may involve significantly higher computational demands. Yet, for system planning, longer runtimes—on the order of several hours—are generally acceptable.

There are two main strategies for using models in planning transitions. One option is to simulate the full evolution of the energy system through time. The alternative is to focus on one or more target years, using a static snapshot model, and combine it with an external algorithm that guides the transition path. In the terminology proposed by Gironès et al. [50], the former is termed a pathway model, while the latter corresponds to a snapshot model—where the system's present state is not explicitly represented.

In their review, Prina et al. [18] evaluated some of the most established energy models based on criteria such as simulation horizon, time-step resolution, sectoral coverage, objective function, and runtime. Their findings revealed that many pathway-oriented models faced key limitations: insufficient temporal granularity, a focus limited to the electricity sector, or high computational burden. To address these issues, Prina et al. opted for the second approach—using a low-complexity snapshot model coupled with an external optimization algorithm.

Specifically, they used EnergyPLAN in combination with a multi-objective evolutionary algorithm (MOEA) to optimize a narrow set of variables: battery capacity, photovoltaic installations, and onshore wind. Although this method reduced runtime and complexity, it failed to meet two of the four key modelling criteria identified earlier. First, it did not allow for the joint optimization of system design and hourly operations over a full year. Second, the tools used were not fully open source. The EnergyPLAN model is a closed simulation platform—available for use, but not for modification or collaborative development.

While such hybrid approaches offer practical solutions for specific planning exercises, none fully satisfy the requirements for open, transparent, temporally detailed, and fully integrated system planning. This reinforces the need for improved models capable of addressing these limitations in a coherent and computationally efficient framework.

Energy models are built with specific structures tailored to different questions. As discussed previously, many models from the literature offer valuable features but share one or more of the following limitations: (i) focus on a single sector—typically electricity—while simplifying others like heating and mobility; (ii) lack of open access or open source availability; (iii) no joint optimization of investment and hourly operation; and (iv) excessive computational time, limiting their suitability for uncertainty analysis.

For instance, DIETER [41] models the electricity sector and partially includes EVs and power-to-heat links, though with simplified representations [20]. ELMOD [51] excludes the transport sector entirely. Of the 54 reviewed models, only 11 include electricity, heat, and mobility. The most well-known is EnergyPLAN [28], which simulates a national-scale, multi-sector energy system.

Access remains a key barrier. Many tools, like PLEXOS [27], support investor decision-making or market analysis, and thus are not fully open. From the 54 models reviewed, 40 are open access, and 29 are both open access and open source. Others aim to become public in the near future.

Another distinction lies in model structure. Simulation models fix assumptions beforehand, while optimization explores many configurations to find the most effective one. Although more flexible, optimization requires more computation—making fast runtimes essential for uncertainty applications.

Models apply different strategies. Some simulate both investment and operation, e.g., EnergyPLAN [28], with very short runtimes.MOthers optimize investment and simulate operation, like GENESYS [52], using evolutionary algorithms. Some optimize only operation, as in Dispa-SET [23]. A few models optimize both investment and operation, such as PLEXOS [27], but tend to be sector-specific due to complexity. Only 16 out of 54 models offer full investment-operation optimization.

Historically, most models focused on single sectors. EMMA [21], for example, analyses flexibility in the European grid but doesn't include heating or mobility—making it unsuitable for integrated planning. Newer models allow partial multi-sector coupling, though often still prioritize one sector and simplify the rest.

Computational time is a decisive factor. For uncertainty studies requiring many simulations, runtimes must be around a minute. EnergyScope TD, for example, takes about 10 seconds for electricity-only and 1 minute for full-sector modelling. Of the 54 models, 25 have runtimes in the minute range; only 11 of these perform optimization, and just 5 include any level of sector coupling.

2.5 EnergyScope Pathway advantages

In response to the identified limitations in existing modelling tools, a new energy system modelling framework based on linear programming (LP) was defined by Limpens in [54]. The model, known as EnergyScope Typical Days (EnergyScope TD), is a significant evolution from an earlier version developed by Moret, Codina Gironès, Maréchal and collaborators [19]. Unlike the previous monthly-based model, EnergyScope Pathway operates at an hourly resolution, enabling a more accurate representation of system dynamics while keeping computation times low thanks to the methodological innovations discussed in the following chapter.

As established in the literature on scenario analysis, the main contribution of EnergyScope TD lies in offering a fully open-source tool—freely downloadable [53]—that can optimize the design and hourly operation of regional or urban energy systems over a full year. The model includes all energy carriers and demands, making it suitable for analyzing cross-sector interactions and evaluating key technologies such as short- and long-term storage, which are critical for the energy transition.

With regard to the criteria outlined in the previous sections: the model treats electricity, heating, and mobility sectors with similar detail; it is open source and ready to use, with pre-loaded data for the Belgian energy system, along with comprehensive documentation and a user guide; it operates on an hourly basis, capturing seasonality and storage needs; and although full-year hourly modelling is computationally intensive, EnergyScope TD reduces complexity by using a representative set of typical days, an approach validated for balancing accuracy and efficiency. This allows the model to simulate systems with high shares of intermittent renewables and diverse storage options in roughly one minute on a standard laptop, making it particularly well-suited for uncertainty analyses.

Due to its computational efficiency and streamlined mathematical formulation, EnergyScope TD also serves as a strong foundation for further development. This has led to the creation of an extended version: EnergyScope Pathway, which is available at [48]. The Pathway version retains the first three strengths of TD—it is open source, includes full-sector representation, and supports hourly operations—while adding a crucial feature: the ability to model investment decisions and system evolution from 2015 to 2050. This makes it a pathway model suitable for system planning. However, this enhancement comes at the cost of increased computational time (several hours per run), limiting its applicability in scenarios requiring extensive sensitivity or uncertainty analysis. The methodology behind EnergyScope Pathway is presented in following chapters.

3. EnergyScope Pathway

This chapter introduces the comprehensive modelling framework developed to support strategic energy transition planning, using a hybrid structure that captures both high-resolution system operation and long-term investment decisions. The model is formulated as a linear programming problem, combining hourly operational detail with a transition pathway from 2025 to 2050. Its ultimate goal is to enable policymakers, researchers, and stakeholders to evaluate realistic, cost-effective, and sustainable roadmaps for decarbonizing the energy system, while accounting for technical constraints, economic trade-offs, and temporal dynamics across multiple planning horizons.

The origins of this model can be traced back to an online calculator developed to foster energy literacy among the general public. Known as EnergyScope Monthly, the initial tool provided a simplified view of national energy systems. Over time, however, it evolved into a more sophisticated model capable of addressing complex policy and technology questions. It has been applied to diverse case studies.

Building upon that foundation, the current and upgraded version introduces several important methodological improvements. Among these are the shift to hourly resolution, the replacement of integer variables with continuous ones for computational efficiency, and the inclusion of new technological dimensions such as energy storage and electric vehicles. This enhanced version enables a more granular analysis of daily and seasonal variations in energy demand and supply, which are critical for understanding the integration challenges posed by intermittent renewable resources, the role of storage technologies, and the operational flexibility required in future energy systems.

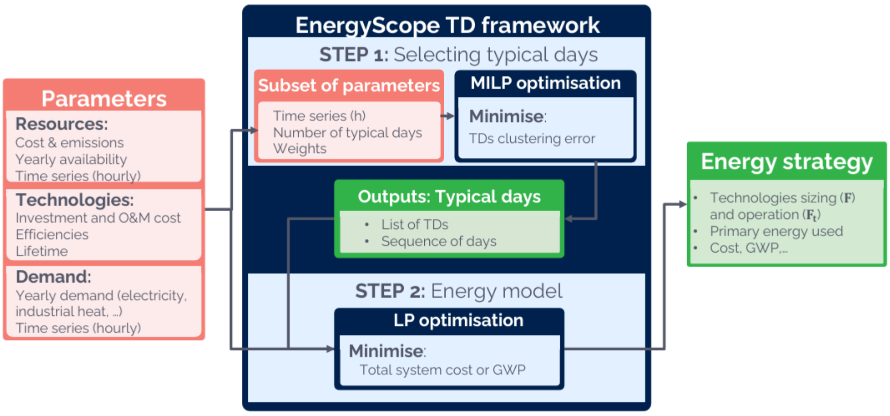

Figure 3.1 – Overview of EnergyScope TD framework

The conceptual flow of the model is illustrated in Figure 3.1. It comprises two main components. First, a selection process identifies a limited set of representative days—called typical days—that approximate the variability of weather and energy demand. Once these typical days are selected, the core of the model solves the energy system's design and dispatch problem. This step determines which technologies should be installed, in what capacities, and how they should be operated throughout the year to minimize either total cost or greenhouse gas emissions. The optimization accounts for all relevant constraints: energy balance, technological efficiencies and potentials, availability of resources, and storage limitations. The result is a detailed snapshot of the optimal energy system configuration, specifying not only the mix of technologies and their installed capacities but also their hourly operational schedules, ensuring that demand is consistently met with the lowest possible environmental or economic impact throughout the year. This pre-processing step reduces the complexity of the optimization problem while preserving the essential temporal dynamics. It is solved using a mixed-integer linear programming approach, minimizing the error introduced by representing the full annual hourly data with a small number of days. This approach ensures a limited an reasonable computational load and captures critical seasonal and daily patterns, providing a robust basis for the subsequent energy system optimization.

The structure outlined above (EnergyScope TD) is powerful but inherently static. It answers what the best system configuration is for a given year but does not explain how to move from today's reality to that optimal future. This is where the model is extended into a dynamic transition framework (Pathway), as depicted in Figure 3.2. In this version, the system is evaluated at key milestones—2025, 2030, 2035, 2040, 2045, and 2050—each representing a major checkpoint along the road to full decarbonization.

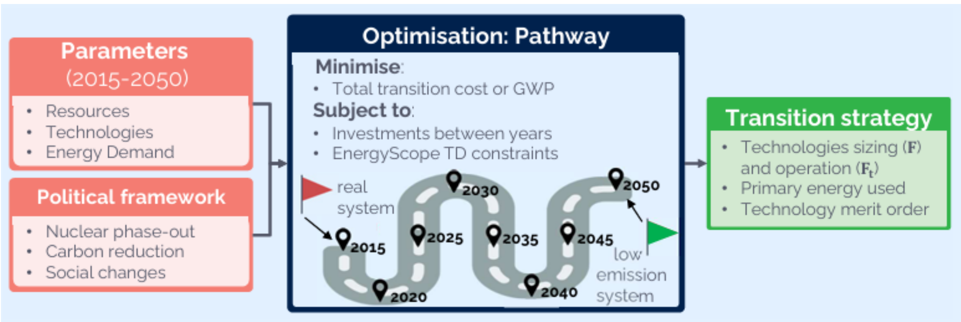

Figure 3.2 – Overview of EnergyScope Pathway framework

The model introduces intertemporal constraints that link decisions across years. These include the decommissioning of technologies after their lifetime, limitations on how quickly new technologies can be adopted, and the possibility to partially decommission technologies before their full lifespan is reached. The structure also tracks cumulative investment and emissions over the entire horizon, allowing for the evaluation of carbon budgets and policy compliance. Importantly, the same energy system formulation applies consistently across all representative years, ensuring coherence in the analysis and enabling a realistic evaluation of transition strategies from current conditions towards the long-term decarbonization objectives.

Four core challenges underpin the design of this dynamic extension. First, it must reconcile different time scales: hours within a day, days within a year, and years across decades. Second, it must manage the ageing and replacement of infrastructure, ensuring continuity in energy services while phasing out outdated technologies. Third, it must incorporate socio-technical inertia—the lag caused by consumer behavior, regulatory frameworks, and supply chain limitations. Fourth, it must distinguish between immediate costs and long-term impacts, clearly differentiating investments made in early phases from those made later, and properly accounting for the evolving environmental and economic implications over the entire transition horizon.

The modelling solution incorporates all these elements in a linear structure, ensuring that it remains computationally tractable while maintaining a high degree of realism. For instance, if electric vehicles are identified as cost-effective, their adoption is modulated over time through constraints that reflect vehicle turnover rates and infrastructure readiness. Similarly, for heating systems, the transition from individual gas boilers to district heating networks is constrained by realistic renovation rates of buildings, available technical workforce, investment cycles, and social acceptance, thereby preventing scenarios that are optimal mathematically but unrealistic in practice. This structured approach allows planners and decision-makers to develop feasible, step-by-step strategies towards decarbonization that align closely with real-world conditions.

An additional innovation is the treatment of investment costs and greenhouse gas emissions across time. All financial flows are discounted using a consistent rate to account for the value of money over time. Meanwhile, emissions are either aggregated yearly or tracked cumulatively to enforce climate targets. This allows for the assessment of strategies that may involve higher upfront costs but lower long-term impacts, or vice versa.

Overall, this modelling approach delivers a coherent and robust framework for guiding energy transition policy. It offers a bridge between long-term visions and near-term decisions, helping to identify the sequence of investments, regulatory steps, and behavioral shifts needed to achieve a carbon-neutral energy system by 2050. It is both flexible and adaptable, making it suitable for diverse national contexts and policy objectives.

In the sections that follow, each component of the framework will be presented, starting with the selection of typical days and their integration into the energy system model. Subsequent sections will delve into the mathematical formulation of constraints, the representation of technologies and resources, and the implementation details that enable the model to deliver actionable insights.

3.1 Typical days selection

In order to simulate an energy system with sufficient accuracy, it is necessary to represent the hourly variability of demand and renewable energy production. However, solving a linear optimization problem over all 8.760 hours in a year is computationally illogical. This challenge is addressed by selecting a subset of representative days—referred to as typical days—which are used to approximate the temporal behavior of the full year. This method enables the model to remain computationally tractable while retaining the essential dynamics required for robust system design and operational analysis.

The typical days are selected based on clustering techniques applied to several key time series. These include electricity and space heating demand, as well as solar irradiance, onshore wind speed, and offshore wind speed. Each time series is normalized and weighted to reflect its relative influence on system operation. A clustering algorithm is then used to group days with similar characteristics. From each group, a single representative day—called the centroid—is selected to stand in for the entire cluster, thereby reducing the data size while maintaining the diversity of temporal profiles.

Figure 3.3 presents a visual interpretation of how typical days are used to reconstruct a synthetic week. Each actual day of the year is assigned to a corresponding typical day, and the sequence is used to model a continuous timeline. In the upper panel of the figure, the storage power is shown, with green areas representing charging events and red areas representing discharging. The lower panel illustrates the evolution of stored energy over the course of a week. This continuous progression of energy levels demonstrates the model's ability to reflect realistic storage dynamics, even when relying on a reduced set of input days.

3.1.1 Clustering and Selection Methods

Several clustering approaches have been developed and evaluated in the literature. Among the most widely used is the k-medoids algorithm, which selects real days from the dataset as cluster centers, thereby preserving the physical interpretability of results. In addition to k-medoids, a more advanced mixed-integer linear programming (MILP) version was introduced by Domínguez-Muñoz et al., offering improved clustering precision at a reduced computational cost. Other methods, such as those proposed by Poncelet et al., rely on minimizing the error in duration curves to better represent the long-term behavior of the time series.

The comparison of these methods is summarized in Table 3.1. According to three performance criteria—computational cost, clustering error, and duration curve error—the Domínguez-Muñoz MILP method demonstrates the most balanced performance. It yields the lowest clustering and duration curve error while maintaining an acceptable computational time. The standard k-medoids method, while simple and fast to implement, results in higher approximation errors. The Poncelet and Poncelet HYB methods perform moderately well but at a higher computational cost, which may not be ideal for scenarios requiring multiple iterations.

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

Table 3.1 – Comparison of different clustering methods for TD selection

Based on this comparison, the Domínguez-Muñoz method is proven to be the most balanced and better option. It provides a reliable trade-off between complexity and accuracy and is particularly suited for scenarios where multiple model runs are required for sensitivity or uncertainty analysis. By minimizing the clustering error and better preserving the structure of the original time series, this method ensures that the selected typical days offer an accurate representation of the year's variability.

3.1.2 Seasonality

While typical days allow for a significant reduction in computational time, they introduce limitations when it comes to modeling inter-day and seasonal dynamics. Traditional formulations treat each typical day independently, which can disrupt the continuity of variables such as storage levels that evolve over time. As a result, technologies that operate over multiple days, such as long-term thermal storage, cannot be accurately represented unless additional measures are implemented.

To address this issue, a reconstruction method has been implemented. A sequence of typical days is constructed such that each day of the year is mapped to one of the selected typical days. The model then computes storage variables across this sequence in a continuous manner. As a result, the energy stored at the end of one day becomes the starting value for the next. This allows for realistic modeling of long-term storage technologies, such as thermal energy buffers or hydrogen systems, which operate across extended periods and are critical for high-renewable energy systems.

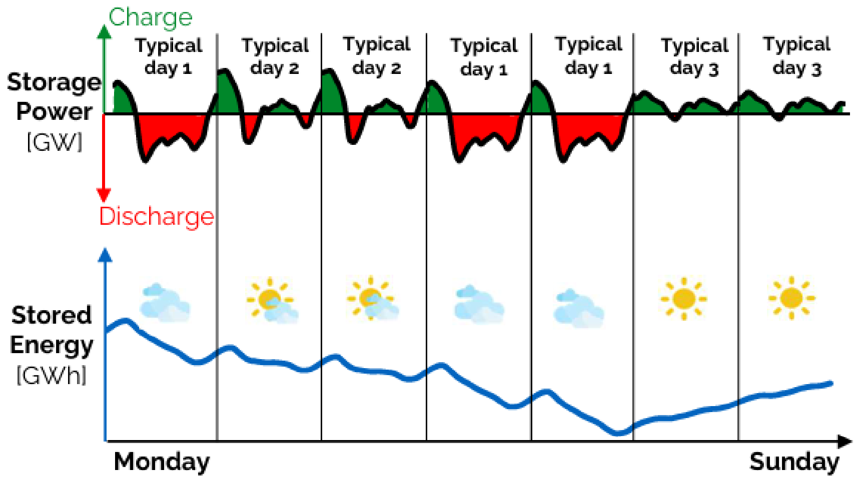

Figure 3.3 – Illustration of TD implementation over a week

The importance of this reconstruction is further emphasized in Figure 3.3. While power dispatch varies by typical day, the energy storage trajectory is smooth and continuous across the week. This modeling detail is essential to capture system flexibility and storage adequacy, particularly in scenarios with high renewable penetration. By ensuring continuity of storage behavior, the model is capable of evaluating the feasibility and value of seasonal storage technologies.

Through the combination of clustering, selection, and temporal reconstruction, the typical day methodology enables the energy system model to maintain a high degree of temporal realism. At the same time, it ensures that computational requirements remain manageable, allowing for the execution of complex transition scenarios across multiple years and under varying assumptions. This methodological foundation provides the necessary flexibility and precision to evaluate strategic decisions in the context of long-term energy planning.

3.2 Energy system model

In this chapter the model is deeply described. Firstly, the model is defined within the nature of a linear programming formulation model. Secondly, the conceptual framework and methodology to face the problem are presented to fully conceptualize how the model is. Thirdly, all the sets, parameters, variables and formulations are described in order to fully define the system and its functioning. Finally, the technological environments and tools used in its application are introduced.

3.2.1 Linear programming formulation

The energy system model is formulated as a linear programming (LP) problem, a mathematical optimization method used to determine the best possible outcome—such as minimizing cost or emissions—given a set of linear relationships and constraints. In an LP problem, both the objective function and the constraints are linear, meaning they involve no powers, products, or nonlinear functions of the decision variables. This structure makes LP a computationally efficient and widely used technique, especially for complex systems with many interacting components.

The LP structure under which EnergyScope is developed, information is articulated under three main concepts: sets, parameters and variables. Sets represent groups of elements, such as the set of available energy resources or technologies (e.g., non-renewable resources, storage technologies…). Parameters are fixed inputs to the model, including values like resource availability or demand profiles. Variables are the decision elements that the model aims to solve for, for example, the installed capacity of wind turbines. Each variable is bounded by a lower and upper limit defined by the model's parameters.

There are two main types of decision variables: independent variables, which the model can choose freely within their bounds, and dependent variables, which are calculated based on constraints involving the independent ones. For example, the investment cost associated with a particular technology is a dependent variable derived from the amount installed, which is an independent variable. Constraints, either equalities (=) or inequalities (<,>), ensure that physical, technical, or policy limitations are respected (e.g., resource limits or deployment limits of a certain technology). Finally, the model includes an objective function, which is a specific quantity to be optimized, typically minimized in this context, such as total system cost or greenhouse gas emissions.

3.2.2 Framework of the system

This chapter presents the structure and optimization strategy of the EnergyScope Pathway model. It is a linear programming-based modelling tool developed to support energy system planning with a high level of detail and transparency. The model is specifically designed to address the challenges of achieving a low-carbon or carbon-neutral energy system by mid-century, considering technological constraints, political limitations and also society behavior. Its formulation enables both annual and long-term planning in a way that is computationally efficient and suitable for scenario analysis under deep decarbonization goals.

The model represents the energy system through a layered framework. These layers act as interfaces between different parts of the system, such as energy production, storage, conversion, and end-use. They ensure that all energy flows are balanced in each time step. The layers are energy carriers themselves, such as electricity or heat, and serve to connect resources to end-use technologies. This layered structure enables the model to be both flexible and detailed, supporting a wide variety of technological interactions and sectoral linkages.

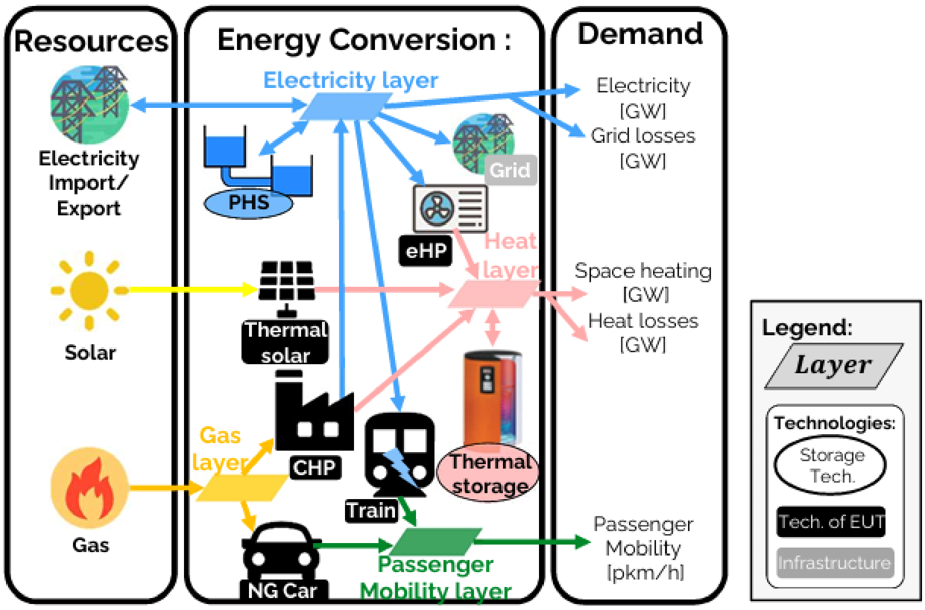

Figure 3.4 – Representation of a generic energy system

As shown in Figure 3.4, the system is conceptually divided into three interconnected parts: resources, energy conversion technologies, and final demand. Resources include energy inputs such as solar energy, natural gas, and electricity imports. These inputs are not consumed directly but must first be processed through conversion technologies. Within the conversion block, technologies such as combined heat and power (CHP) units, thermal solar panels, and electric heat pumps (eHP) transform the raw energy resources into usable forms. These transformed energy carriers then flow into the appropriate layers, where they are distributed to meet specific demands, such as electricity for households, heat for space heating, or fuel for mobility services.

The model includes three main types of technologies. The first are end-use conversion technologies, which deliver final energy services to consumers, such as electric cars, industrial boilers, means of transport, photovoltaic technologies, combined cycle plants, and CHP units. The second are storage technologies, which store energy in one time period and release it in another, helping to manage the variability of both demand and renewable energy production. These include, for instance, thermal storage and batteries. The third type are infrastructure technologies, which facilitate the physical distribution of energy, such as electricity grids or district heating networks. Each technology type interacts with the relevant energy layer and contributes to the balance of supply and demand within that layer.

The more detailed structure of the energy system is captured in Figure 3.7. This illustration presents a comprehensive view of the model's full architecture, highlighting the numerous technologies and their interactions across energy carriers. Electricity, for instance, can be generated from a variety of sources including photovoltaic panels, hydro-river plants, wind turbines, geothermal stations, supercritical fossil units, integrated gasification combined cycle units, and nuclear power. The electricity generated is then used to meet direct electricity demands, power transport systems such as trains or electric vehicles, or is converted into synthetic fuels and hydrogen. It can also be stored using batteries or pumped hydro systems and later used when demand is high.

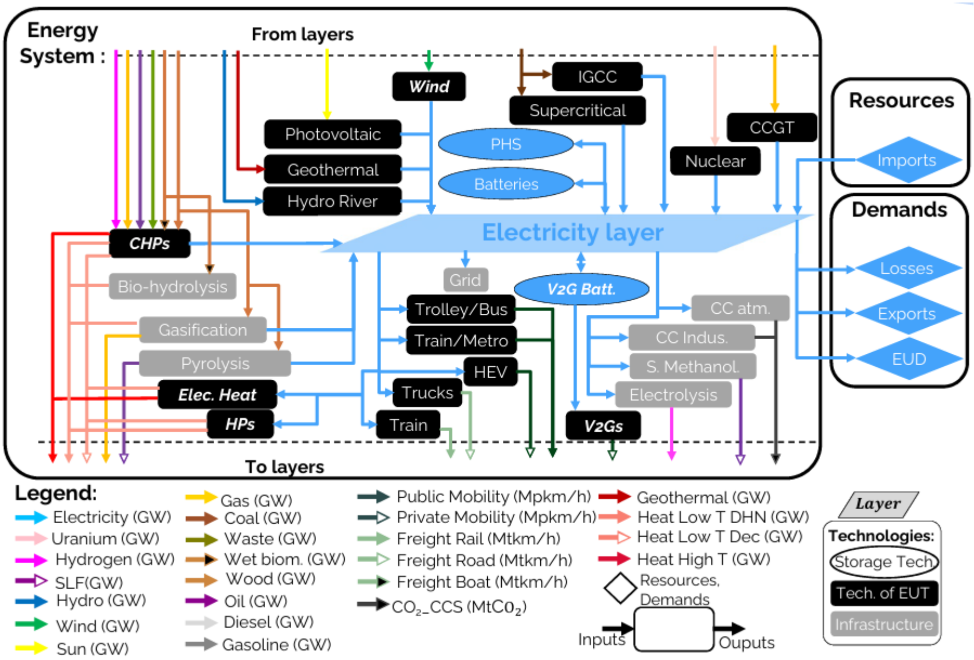

Figure 3.5 – Representation od the electricity layer interconnections

The model also allows for indirect links between sectors. For example, electricity can be converted into hydrogen via electrolysis, which in turn can be used in fuel cell vehicles or for industrial processes. Waste heat from certain technologies can be redirected to supply heating needs. In this way, the model captures the potential for sector coupling, where one sector (e.g. electricity) supports another (e.g. mobility or heating), thereby increasing overall system efficiency and flexibility. These interactions are central to planning a resilient and low-carbon energy transition.

The mathematical formulation of the model is based on a set-based structure, which allows it to remain consistent and scalable. This structure is depicted in Figure 3.5, where each key component—resources, technologies, energy carriers (layers), and end-use categories—is organised into a set. These sets define the relationships between entities and how they interact over time. Each technology is assigned a place within the appropriate layer and associated with specific energy services. For instance, an electric vehicle is connected to the electricity layer and serves passenger mobility demand, while a gas boiler is associated with the gas layer and supplies low-temperature heat.

In terms of time resolution, the model operates with hourly granularity using a selection of typical days, which represent seasonal and daily patterns in demand and supply. By capturing both daily and seasonal variability, the model ensures that energy systems with high shares of intermittent renewable sources, such as wind and solar, can be realistically evaluated.

The EnergyScope Pathway model does not only assess a single year but extends this analysis to simulate the evolution of the energy system over time. As shown in Figure 3.2, the time horizon is broken down into a series of representative years, in this case, five years from an initial point 2025 up to 2050. For each of these years, a full optimization is performed using updated data on technology costs, resource availability, energy demands, and emissions targets. What makes this a "pathway" model is the way these representative years are linked through constraints that govern investments, technology decommissionings, and operational limitations.

The model carefully tracks how technologies are deployed, replaced, or phased out over time. If a technology is installed in one period, it can continue operating in the next, unless it is decommissioned early or reaches the end of its lifetime. In cases where a technology is still operational beyond the final year of the model (2050), the residual value of that investment is accounted for to avoid penalizing long lasting infrastructure. This salvage value is particularly important for technologies such as power grids or heat networks, which may have lifespans longer than the modelled horizon.

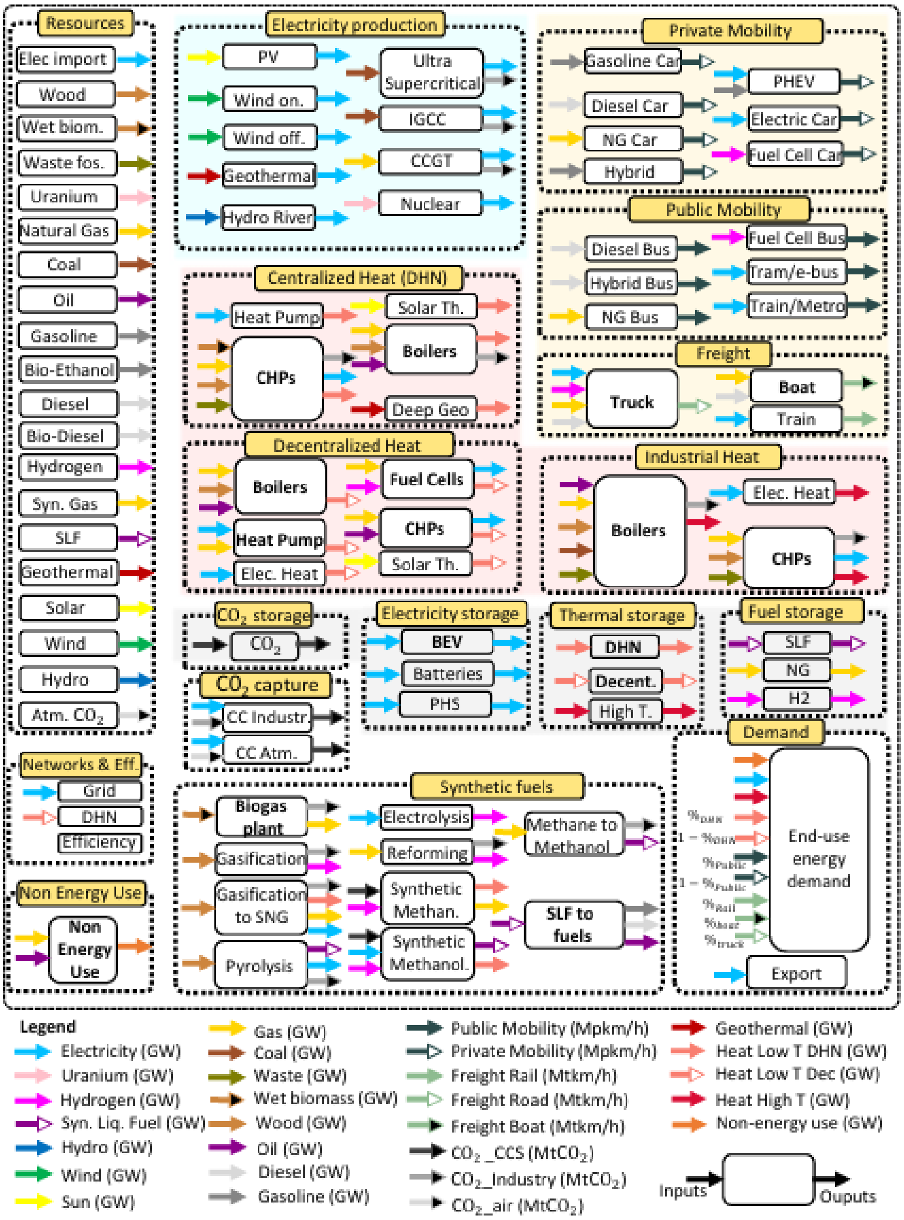

Figure 3.6 – Representation of the model's relationships

A notable feature of the pathway formulation is how it represents societal inertia—the fact that large-scale energy transitions take time and cannot happen instantly. For example, replacing all private cars with electric vehicles is not feasible in just a few years due to market limitations, manufacturing capacity, and user acceptance. To reflect this, the model introduces constraints on how much a sector can change between two time periods. This applies to key sectors like passenger transport, freight, and heating, where abrupt transitions are not realistic. These constraints help produce more plausible, policy-relevant transition pathways.

The model's objective function over the full transition is to minimize the total cost, which includes capital investment costs, operational and maintenance costs, and the cost of energy resources. Alternatively, the model can be used to minimize total greenhouse gas emissions or apply emissions caps, ensuring that the selected pathway remains within a specific carbon budget. This makes it well suited for planning according to climate policy goals, such as those set by the European Union for net-zero emissions by 2050.

In conclusion, the EnergyScope Pathway model offers a detailed and structured representation of how a regional energy system can evolve over time to meet long-term decarbonization targets. It accounts for interactions across energy sectors, technological and physical constraints, storage, and infrastructure needs. Its ability to model sector coupling, time-dependent transitions, and societal inertia make it a powerful tool for policymakers and researchers. Figures 3.1 through 3.7 illustrate how the model connects resources, technologies, and demands through layered structures and long-term optimization logic. This framework enables the design of cost-effective, technically feasible, and socially realistic energy transition Pathway.

3.2.3 Sets, parameters and variables

In the EnergyScope Pathway model, three fundamental concepts organize the structure of the formulation: sets, parameters, and variables. These elements are essential for correctly defining and solving the optimization problem and are consistently used throughout the implementation.

A set defines the domain over which other components are indexed. It contains discrete elements such as technologies, representative years, or time steps. For example, the set TECHNOLOGIES includes all available technologies in the system, while YEARS refers to the representative years during which the EnergyScope TD model is evaluated. Sets serve as the structure for looping over elements in equations and data.

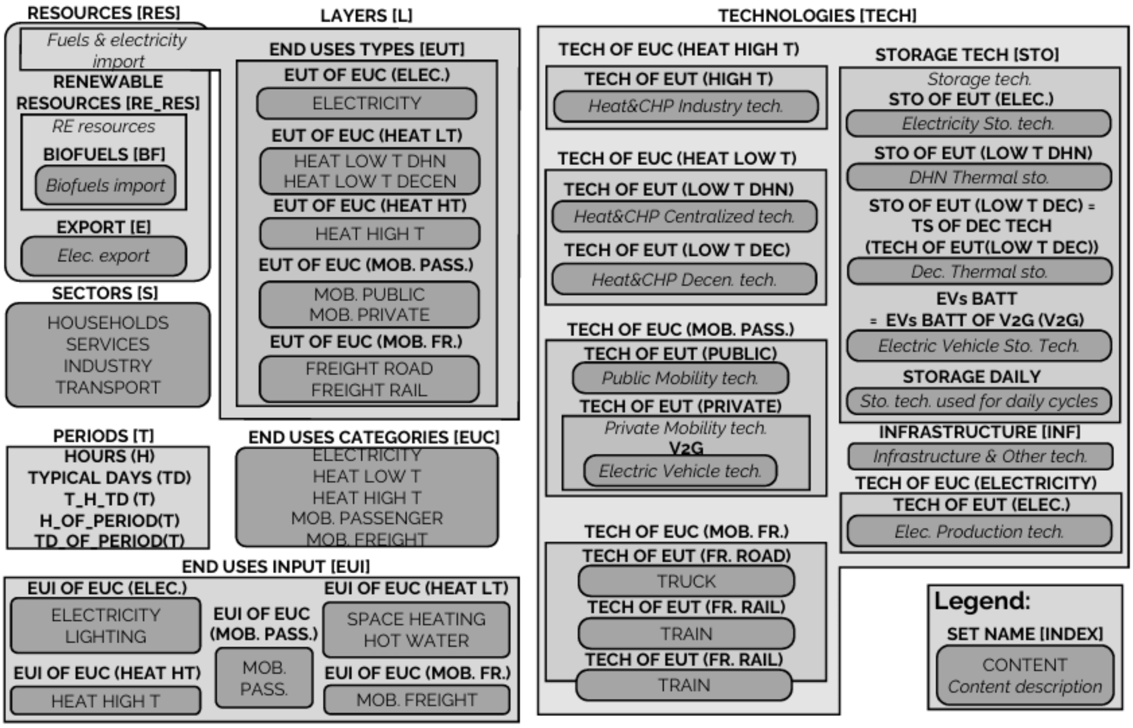

Figure 3.7 – Representation of the SETs' structure in EnergyScope TD

The following table (3.1) resumes all the sets not accounted in the figure 3.7 but still necessary for the application of EnergyScope Pathway.

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

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

Table 3.1 – SETs crated for the EnergyScope Pathway version

A parameter provides the model with fixed input data. These are known values before solving the optimization problem and are often based on technical, economic, or environmental assumptions. Examples include c_{inv}(y, tech) representing the investment cost of a technology in a given year, or $GWP_{limit,transition}$ defining the maximum allowed greenhouse gas emissions over the full transition period. Parameters can be scalar or indexed over one or multiple sets and typically originate from empirical data, forecasts, or policy assumptions.

Parameter	Units	Description
τ (tech)	[-]	Investment cost annualization factor
i_{rate}	[-]	Real discount rate
$endUses_{year}$ (eui, s)	[GWh/y],[Mpkm], [Mtkm]	Annual end-uses in energy services per sector
endUsesInput (eui)	[GWh/y],[Mpkm], [Mtkm]	Total annual end-uses in energy services
re_{share}	[-]	minimum share [0;1] of primary RE
GWP_{limit}	[ktCO2-eq/y]	Higher CO2-eq emissions limit
$\%_{public,min}$ $\%_{public,max}$	[-]	Lower and upper limit to $\%_{Public}$
$\%_{fr,rail,min}$ $\%_{fr,rail,max}$	[-]	Lower and upper limit to $\%_{Fr,Rail}$
$\%_{fr,boat,min}$ $\%_{fr,boat,max}$	[-]	Lower and upper limit to $\%_{Fr,Boat}$
$\%_{fr,truck,min}$ $\%_{fr,truck,max}$	[-]	Lower and upper limit to $\%_{Fr,Truck}$
$\%_{dhn,min}$ $\%_{dhn,max}$	[-]	Lower and upper limit to $\%_{DHN}$
t_{op}(h, td)	[h]	Time period duration (default 1h)
f_{min}, f_{max}(tech)	[GW],[GWh],[Mpkm], [Mtkm]	Min./max. installed size of the technology
$f_{min\%}$, $f_{max,\%(}$tech)	[-]	Min./max. relative share of a technology in a layer
avail(res)	[GWh/y]	Resource yearly total availability
c_op(res)	[M€2015/GWh]	Specific cost of resources
veh_{capa}	[km-pass/h/veh.] ,[Mpkm],[Mtkm]	Mobility capacity per vehicle
$\%_{peak,sh}$	[-]	Ratio peak/max. space heating demand in typical days
f(resUtech\sto, l)	[GW],[Mpkm/h], [Mtkm/h]	Input from (<0) or output to (>0) layer/resource.
c_{inv}(tech)	[M€$_{2015}$/GW] [M€$_{2015}$/GWh], [M€$_{2015}$/Mpkm/h],[M€$_{2015}$/Mtkm /h]	Technology specific investment cost
c_{maint}(tech)	[M€$_{2015}$/GW/y] [M€$_{2015}$/GWh/y], [M€$_{2015}$/Mpkm/h/y],[M€$_{2015}$/Mtk m/h/y]	Technology specific yearly maintenance cost
lifetime(tech)	[y]	Technology lifetime
GWP_{constr}(tech)	[ktCO2eq./GW],[ktCO2eq./GW h],[ktCO2eq./Mpkm], [ktCO2eq./Mtkm]	Technology construction specific GWP emissions
GWP_{op}(res)	[ktCO2-eq./GWh]	Specific GHG emissions of resources

$c_p(tech)$	[-]	Yearly capacity factor
$\eta_{sto,in}$, $\eta_{sto,out}(sto, l)$	[-]	Efficiency [0;1] of storage input/output to layer. Set to 0 if storage not related to layer.
$\%_{sto,loss}(sto)$	[1/h]	Losses in storage (self discharge)
$t_{sto,in}(sto)$	[-]	Time to charge storage (Energy to power ratio)
$t_{sto,out}(sto)$	[-]	Time to discharge storage (Energy to power ratio)
$\%_{avail}$ (sto)	[-]	Storage technology availability to charge/discharge
$\%_{net,loss}(eut)$	[-]	Losses coefficient [0;1] in the networks (grid and DHN)
$eV_{batt,size}$	[GWh]	Battery size per V2G car technology
$c_{grid,extra}$	[M€$_{2015}$/GW]	Cost to reinforce the grid per GW of intermittent renewable
$elec_{import,max}$	[GW]	Maximum net transfer capacity
$solar_{area}$	[km²]	Available area for solar panels
$powerdensity_{PV}$	[GW/km²]	Peak power density of PV
$Powerdensity_{solar,thermal}$	[GW/km²]	Peak power density of solar thermal
$\%_{elec}(h,td)$	[-]	Yearly time series (adding up to 1) of electricity end-uses
$\%_{sh}(h,td)$	[-]	Yearly time series (adding up to 1) of SH end-uses
$\%_{pass}(h,td)$	[-]	Yearly time series (adding up to 1) of passenger mobility end-uses
$\%_{fr}(h,td)$	[-]	Yearly time series (adding up to 1) of freight mobility end-uses
$c_{p,t}(tech, h, td)$	[-]	Hourly maximum capacity factor for each technology (default 1)
$max_{inv,phase}(p)$	[M€$_{2015}$]	Maximum investment per phase
t_{phase}	[years]	Phase period (default 5 years)
$diff_{2015,phase}(p)$	[years]	Years difference between financial reference year (2015) and the phase
$GWP_{budeget}$	[ktCO2]	Maximum CO_2eq emissions during the transition.

$decom_{allowed}$(p,p,tech)	[-]	Allow a technology to be decommissioned
$limit_{LT,renovation}$	[-]	Limit the change in low-temperature heat technologies during a phase
$limit_{pass.mob,changes}$	[-]	Limit the change in passenger mobility technologies during a phase
$limit_{freight,changes}$	[-]	Limit the change in freight mobility technologies during a phase
efficiency(y)	[-]	Share of energy efficiency achievement compared to reference (2050).

Table 3.2 – Definition of parameters

A variable, in contrast, is the unknown the model must determine to achieve the objective function under given constraints. For instance, F(y, tech) represents the installed capacity of a technology in a given year, and F_t(y, tech, h, td) its hourly use. These variables are subject to optimization. In EnergyScope Pathway, all variables are continuous and non-negative unless specified otherwise.

Variable	Units	Descripion
$\%_{Public}$	[-]	Ratio [0;1] public mobility over total passenger mobility
$\%_{Fr,Rail}$	[-]	Ratio [0;1] rail transport over total freight transport
$\%_{Fr,Boat}$	[-]	Ratio [0;1] boat transport over total freight transport
$\%_{Fr,Truck}$	[-]	Ratio [0;1] truck transport over total freight transport
$\%_{DHN}$	[-]	Ratio [0;1] centralized over total low-temperature heat
F(tech)	[GW] , [GWh], [Mpkm], [Mtkm]	Installed capacity with respect to main output
F_t(tech ∪ res, h, td)	[GW]	Operation in each period
Sto_{in}, Sto_{out}(sto, l, h, td)	[GW]	Input to/output from storage units
$P_{Nuclear}$	[GW]	Constant load of nuclear
$\%_{PassMob}$(TECH OF EUC(PassMob))	[-]	Constant share of passenger mobility
$\%_{FreightMob}$(TECH OF EUC(FreightMob))	[-]	Constant share of freight mobility
$\%_{HeatDEC}$(TECH OF EUC(HeatLowTDEC)\{DecSolar})	[-]	Constant share of low temperature heat decentralised supplied by a technology plus its associated thermal solar and storage

F_{Sol}(TECH OF EUC(HeatLowTDEC)\{DecSolar})	[GW]	Solar thermal installed capacity associated to a decentralised heating technology
F_{tSol}(TECH OF EUC(HeatLowTDEC)\{DecSolar})	[GW]	Solar thermal operation in each period
EndUses(l, h, td)	[GW], Mpkm], [Mtkm]	End-uses demand. Set to 0 if $l \notin$ EUT
C_{tot}	[M€/y]	Total annual cost of the energy system
C_{inv}(tech)	[M€]	Technology total investment cost
C_{maint}(tech)	[M€/y]	Technology yearly maintenance cost
C_{op}(res)	[M€/y]	Total cost of resources
GWP_{tot}	[ktCO_2-eq./y]	Total yearly GHG emissions of the energy system
GWP_{constr}(tech)	[ktCO_2-eq.]	Technology construction GHG emissions
GWP_{op}(res)	[ktCO_2-eq./y]	Total GHG emissions of resources
Net_{loss}(eut, h, td)	[GW]	Losses in the networks (grid and DHN)
Sto_{level}(sto, t)	[GWh]	Energy stored over the year
F_{new}(p, tech)	[GW]	Installed capacity during a phase with respect to the main output
F_{decom}(p, p*, tech)	[GW]	Decommissioned capacity during a phase with respect to the main output
F_{old}(p, tech)	[GW]	Retired capacity during a phase with respect to the main output
Cinv,phase(p)	[M€/GW]	Phase total annualised investment cost
C_{opex}(y)	[M€/GW]	Operational expenditure over a year
$C_{tot,opex}$	[M€/GW]	Total operational expenditure over the transition
$C_{tot,capex}$	[M€/GW]	Total capital expenditure over the transition
$C_{tot,trans}$	[M€/GW]	Total transition cost
$GWP_{transition}$	[MtCO_2]	Total transition global warming potential
Δ_{change}(p, tech)	[GW]	Change in a technology used during a phase

Table 3.3 – Definition of variables

In summary, sets define the structure of the model, parameters feed it with data, and variables are the core elements optimized by the solver. Together, they form the formal language through which the energy system is represented and analyzed in the EnergyScope framework.

3.2.4 Formulation of the model

In this chapter, the mathematical formulations used in the modeling framework are presented and explained. These formulas serve to quantify costs, emissions, and resource flows within the analyzed energy transition scenarios. Computational relationships between variables are defined to establish the basis for simulating investment, operational, and environmental outcomes. By formalizing these equations, transparency and reproducibility of the modeling process are ensured, allowing the derivation of results to be systematically traced from initial assumptions.

Cost related equations

The total system cost in Eq. (1) captures all yearly expenses required to operate the energy system in year *y*. It combines three components: annualized investment costs in technologies (using the annuity factor tau (τ), operation and maintenance costs, and the cost of resource use. This formulation ensures that both fixed infrastructure and variable expenditures are accounted for, allowing for consistent cost comparison across different years and scenarios.

$$\mathrm{C}_{\mathrm{tot}}(y) = \sum_{j \in \mathrm{TECH}} \left(\tau(y,j) \cdot \mathrm{C}_{\mathrm{inv}}(y,j) + \mathrm{C}_{\mathrm{maint}}(y,j)\right) + \sum_{i \in \mathrm{RES}} \mathrm{C}_{\mathrm{op}}(y,i) \quad \forall y \in \mathrm{YEARS} \tag{1}$$

The investment cost for each technology j in year y is quantified in Eq. (2). It results from multiplying the unit capital cost c_{inv} (y, j) by the corresponding installed capacity F(y, j). This approach allows the model to reflect the total capital required for technology deployment.

$$C_{\mathrm{inv}}(y,j) = c_{\mathrm{inv}}(y,j) \cdot F(y,j) \quad \forall y \in \mathrm{YEARS},\ j \in \mathrm{TECH} \tag{2}$$

Eq. (3) describes the annual costs related to the operation and maintenance of each technology. It multiplies the specific cost rate c_{maint}(y, j) with the installed capacity F(y, j), ensuring these recurring expenses are integrated into system evaluations.

$$C_{\mathrm{maint}}(y,j) = c_{\mathrm{maint}}(y,j) \cdot F(y,j) \quad \forall y \in \mathrm{YEARS},\ j \in \mathrm{TECH} \tag{3}$$

Annual resource usage costs are represented in Eq. (4). The model calculates these by multiplying the unit cost c_{op}(y, i) by the total resource consumption Res(y, i), capturing variable expenditures such as fuel or electricity imports.

$$C_{\mathrm{op}}(y,i) = c_{\mathrm{op}}(y,i) \cdot \mathrm{Res}(y,i) \quad \forall y \in \mathrm{YEARS},\ i \in \mathrm{RES} \tag{4}$$

Emissions related equations

In Eq. (5), the model aggregates the total greenhouse gas emissions resulting from resource consumption in year y. It does so by summing the operational GWP contributions $\mathrm{GWP}_{\mathrm{op}}(y, i)$ across all resources $i \in \mathrm{RES}$. This approach ensures that all emissions directly tied to resource usage are accounted for in the environmental evaluation.

$$\mathrm{GWP}_{\mathrm{tot}}(y) = \sum_{i \in \mathrm{RES}} \mathrm{GWP}_{\mathrm{op}}(y,i) \quad \forall y \in \mathrm{YEARS} \tag{5}$$

Construction-related emissions are captured in Eq. (6), where the specific GWP factor $\mathrm{gwp}_{\mathrm{constr}}(y, j)$ is multiplied by the installed capacity F(y, j) for each technology j. This term reflects the indirect environmental impact of infrastructure development, which is crucial for life-cycle assessment. This equations serves a purpose when the whole LCA is evaluated in the study, however, in this study only GWP associated to the operation of the technologies is accounted,

$$\mathrm{GWP}_{\mathrm{constr}}(y,j) = \mathrm{gwp}_{\mathrm{constr}}(y,j) \cdot F(y,j) \quad \forall y \in \mathrm{YEARS},\ j \in \mathrm{TECH} \tag{6}$$

Equation 7 quantifies emissions generated from resource operation by combining the emission factor $\mathrm{gwp}_{\mathrm{op}}(y, i)$ with the total resource use Res(y, i). This component captures the direct, fuel-based contributions to the system's overall GHG footprint.

$$\mathrm{GWP}_{\mathrm{op}}(y,i) = \mathrm{gwp}_{\mathrm{op}}(y,i) \cdot \mathrm{Res}(y,i) \quad \forall y \in \mathrm{YEARS},\ i \in \mathrm{RES} \tag{7}$$

The cumulative greenhouse gas emissions over the entire transition period are computed in Eq. (8). It starts with the base year (2025) and adds a time-weighted average of emissions for each phase. This method ensures temporal consistency and a realistic assessment of climate impact across the planning horizon.

$$\mathrm{GWP}_{\mathrm{transition}} = \mathrm{GWP}_{\mathrm{tot}}(2025) + \sum_{p \in \mathrm{PHASE}} t_{\mathrm{phase}} \cdot \frac{\mathrm{GWP}_{\mathrm{tot}}(y_{\mathrm{start}}(p)) + \mathrm{GWP}_{\mathrm{tot}}(y_{\mathrm{stop}}(p))}{2} \tag{8}$$

Technology sizing constraints

This constraint defines lower and upper bounds on the installed capacity of each technology. For any year y and technology j, the value of $F_{(y,\,j)}$ must remain between $f_{\mathrm{min}}(y, j)$ and $f_{\mathrm{max}}(y, j)$. This ensures realistic technology scaling, reflecting practical constraints such as physical limits or policy targets.

$$f_{\min}(y,j) \leq F(y,j) \leq f_{\max}(y,j) \quad \forall y \in \text{YEARS},\ j \in \text{TECH} \tag{9}$$

To enforce a realistic upper limit on hourly output, Eq. (10) relates installed capacity to time-dependent generation. The hourly production F_t(y, j, h, td) is limited by the product of $F_{(y, j)}$ and the capacity factor $c_{p,t}$(y, j, h, td). This is particularly important for variable renewables that depend on hourly resource availability.

$$F_t(y,j,h,td) \leq F(y,j) \cdot c_{p,t}(y,j,h,td) \tag{10}$$

$$\forall y \in \text{YEARS},\ j \in \text{TECH},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Annual production is constrained in Eq. (11) by summing hourly outputs across all periods, hours, and typical days. The total sum of F_t(y, j, h, td) × t_{op}(h, td) must not exceed the annual capacity limit defined by $F_{(y, j)}$ × c_p(y, j) × totaltime. This guarantees consistency between hourly dispatch and realistic yearly performance.

$$\sum_{t,h,td} F_t(y,j,h,td) \cdot t_{\text{op}}(h,td) \leq F(y,j) \cdot c_p(y,j) \cdot t_{\text{op}} \quad \forall y \in \text{YEARS},\ j \in \text{TECH} \tag{11}$$

Resourse constraint

$$\text{Res}(y,i) \leq \text{avail}(y,i) \quad \forall y \in \text{YEARS},\ i \in \text{RES} \tag{12}$$

Equation 12 places a yearly upper limit on the use of each resource. The total quantity consumed Res(y, i) must not exceed the available quantity avail(y, i). This guarantees that resource consumption remains within physical or regulated limits, such as availability of domestic fuels, import capacity, or environmental constraints.

Layer balance constraint

$$\sum_{i \in \text{RES} \cup \text{TECH} \setminus \text{STO}} f(y,i,l) \cdot F_t(y,i,h,td) + \sum_{j \in \text{STO}} (\text{Sto}_{\text{out}}(y,j,l,h,td) - \text{Sto}_{\text{in}}(y,j,l,h,td)) -$$

$$- \text{EndUses}(y,l,h,td) = 0 \tag{13}$$

$$\forall\, y \in \text{YEARS},\ l \in \text{LAYERS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Equation 13 ensures energy balance across each energy layer l for every hour h and typical day td within a given year y. The first term represents the net input or output of energy from all technologies and resources (excluding storage), computed as the product of a directional coefficient f(y, i, l) and the hourly output F_t(y, i, h, td), where f(y, i, l) equals 1 or a positive value if the resource or technology delivers energy to layer l, or a negative value if it consumes from it. The second term accounts for storage flows, where energy extracted from storage is given by Sto_{out}(y, j, l, h, td) and energy injected is represented by Sto_{in}(y, j, l, h, td). Their difference gives the net storage contribution in that layer and time step. The last term EndUses(y, l, h, td) reflects the demand in layer l at the given moment, defaulting to zero for non-end-use layers. Altogether, this equation ensures that supply from technologies, resources, and storage exactly matches demand in each energy layer and time slice, maintaining a consistent energy balance across the system.

Storage related constraints

This constraint models the evolution of energy stored in a storage unit j during period t of year y. The state of charge Sto_{level}(y, j, t) depends on the previous level Sto_{level}(y, j, t-1), reduced by storage losses sto_{loss}(y, j), and adjusted by the net energy exchanged in the current step. This exchange is scaled by the operation time t_{op}(h, td) and includes both energy injected into storage Sto_{in}(y, j, l, h, td) multiplied by the charging efficiency $\eta_{sto,in}$(y, j, l), and energy extracted from storage Sto_{out}(y, j, l, h, td) divided by the discharging efficiency $\eta_{sto,out}$(y, j, l). Together, these elements ensure that the model accurately tracks storage behavior over time, incorporating both energy losses and efficiency constraints across all the hours in each typical day.

$$\mathrm{Sto}_{\mathrm{level}}(y,j,t) = \mathrm{Sto}_{\mathrm{level}}(y,j,t{-}1)\cdot(1-\%\mathrm{sto}_{\mathrm{loss}}(y,j)) +$$

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

$$\forall y\in \mathrm{YEARS},\ j\in \mathrm{STO},\ t\in \mathrm{PER},\ h\in \mathrm{HOURS},\ td\in \mathrm{TYPICAL\ DAYS} \tag{14}$$

To model daily storage technologies, the storage level is directly linked to the hourly operational flow. Equation (15) imposes that the energy level stored in a unit j on day t of year y equals the energy charged or discharged in that same time step. This assumption simplifies the dynamics of fast-response systems such as batteries or thermal storage, ensuring that storage cycles are confined to the same day and not carried across periods.

$$\mathrm{Sto}_{\mathrm{level}}(y,j,t) = F_t(y,j,h,td) \tag{15}$$

$$\forall y \in \text{YEARS},\ j \in \text{STORAGE DAILY},\ t \in T,\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

For seasonal or long-duration storage systems, Equation (16) enforces that the energy stored at any given time does not exceed the installed storage capacity. This applies to technologies that allow inter-day or seasonal shifting, such as hydro reservoirs or large-scale thermal storage.

$$\text{Sto}_{\text{level}}(y,j,t) \leq F(y,j) \quad \forall y \in \text{YEARS},\ j \in \text{STORAGE} \setminus \text{STORAGE DAILY},\ t \in T \tag{16}$$

These constraints ensure that storage technologies only interact with energy layers to which they are technically connected. If a storage system has zero input or output efficiency for a particular layer, it is treated as entirely disconnected from that layer. This prevents any energy transfer into or out of the storage unit under such conditions. As a result, only meaningful exchanges, those with defined efficiency, are allowed, maintaining physical realism in the model's representation of storage-layer coupling.

$$\text{if } \eta_{\text{sto,in}}(y,j,l) = 0 \text{ then } \text{Sto}_{\text{in}}(y,j,l,h,td) = 0 \tag{17}$$

$$\text{if } \eta_{\text{sto,out}}(y,j,l) = 0 \text{ then } \text{Sto}_{\text{out}}(y,j,l,h,td) = 0 \tag{18}$$

$$\forall y \in \text{YEARS},\ j \in \text{STORAGE},\ l \in \text{LAYERS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

The following constraint (eq.19) ensures that the energy being charged into and discharged from stationary storage units does not exceed what is physically feasible given the system's power capacity and available energy content. The charging and discharging terms are weighted by their respective durations, and the result must remain within the product of installed energy capacity F(y, j) and the availability ratio $\text{sto}_{\text{avail}}$ (y, j). This condition is essential to represent operational limits for technologies excluding BEVs or PHEVs.

$$\text{Sto}_{\text{in}}(y,j,l,h,td) \cdot t_{\text{sto,in}}(y,j) + \text{Sto}_{\text{out}}(y,j,l,h,td) \cdot t_{\text{sto,out}}(y,j) \leq F(y,j) \cdot \%\text{sto}_{\text{avail}}(y,j)$$

$$\forall y \in \text{YEARS},\ j \in \text{STORAGE} \setminus \{\text{BEV BATT}, \text{PHEV BATT}\},\ l \in \text{LAYERS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS} \tag{19}$$

In the case of vehicle-integrated storage, the available capacity is further reduced to reflect mobility requirements. The term involving F_t(y, i, h, td) accounts for electricity used in transport, scaled by vehicle capacity and battery size per car. The discharge side combines conventional storage output with net electricity exchange from the vehicle fleet, all subject to the same power-duration logic. By incorporating these adjustments, the model captures how V2G systems contribute to the grid only when physically present and not in use for mobility.

$$\text{Sto}_{\text{in}}(y,j,l,h,td) \cdot t_{\text{sto,in}}(y,j) + [\text{Sto}_{\text{out}}(y,j,l,h,td) + \tag{20}$$

$$+ f(i, \text{Electricity}) \cdot F_t(y, i, h, td)] \cdot t_{\text{sto,out}}(y, j) \leq \left[F(y, j) - \frac{F_t(y, i, h, td)}{v_{\text{cap}}(y, i)} \cdot b_{\text{car}}(y, i)\right] \cdot \%\text{sto}_{\text{avail}}(y, j)$$

$$\forall y \in \text{YEARS},\ i \in \text{V2G},\ j \in \text{EVs BATT OF V2G}(i),\ l \in \text{LAYERS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Constraints related to infrastructure

In Equation (21), the term $\text{net}_{\text{losses}}$(y, e, h, td) captures the network losses associated with delivering energy to each end-use type. This value is computed by summing the output from all contributing technologies and resources into the specified EUT e, then multiplying by loss_{net}(y, e), a predefined loss factor. Only technologies with a positive contribution to the layer are included. This helps model grid inefficiencies in systems like electricity or district heating, where losses can be non-negligible.

$$\text{Net}_{\text{losses}}(y, e, h, td) = \left(\sum_{j \in \text{RES} \cup \text{TECH} \setminus \text{STO} | f(y,j,e) > 0} f(y, j, e) \cdot F_t(y, j, h, td)\right) \cdot \%\text{loss}_{\text{net}}(y, e) \quad (21)$$

$$\forall y \in \text{YEARS},\ e \in \text{EUT},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Equation (22) ensures that the size of the electrical grid accounts for the integration of intermittent renewables. The installed grid capacity F(y, Grid) must increase proportionally with the added capacity of $\text{WIND}_{\text{onshore}}$, $\text{WIND}_{\text{offshore}}$, and PV, beyond their defined minimum thresholds. The proportionality factor reflects the additional infrastructure cost per GW integrated, represented by cgrid,extra / cinv(y, Grid). This ensures that reinforcement costs are accounted for when expanding renewable deployment.

$$F(y, \text{Grid}) \geq 1 + \left(\frac{c_{\text{grid,extra}}}{c_{\text{inv}}(y, \text{Grid})}\right) \cdot [F(y, \text{WIND}_{\text{onshore}}) + F(y, \text{WIND}_{\text{offshore}}) + F(y, \text{PV}) -$$

$$- f_{\text{min}}(y, \text{WIND}_{\text{onshore}}) - f_{\text{min}}(y, \text{WIND}_{\text{offshore}}) - f_{\text{min}}(y, \text{PV})] \quad \forall y \in \text{YEARS} \quad (22)$$

For district heating networks, Equation (23) calculates the required infrastructure size based on the heat output supplied to the $\text{HEAT}_{\text{LT,DHN}}$ layer. It aggregates the energy from all relevant non-storage technologies, each weighted by its corresponding conversion coefficient f. This approach ties infrastructure cost directly to actual system usage, rather than assuming a fixed network size.

$$F(y, \text{DHN}) = \sum_{j \in \text{TECH} \setminus \text{STO} | f(y,j,\text{HEAT}_{\text{lowT,DHN}}) > 0} f(y, j, \text{HEAT}_{\text{lowT,DHN}}) \cdot F(y, j) \quad \forall y \in \text{YEARS} \quad (23)$$

End-use demand constraints

Hourly demand for each energy layer l is computed by disaggregating annual demand inputs using dedicated time series and structural parameters. For electricity, the model combines a flat base load, End Uses Input(y, l) divided by t_{op}, with a dynamic lighting profile modulated by $\%_{elec}(h, td)$ and scaled by $t_{op}(h, td)$. Heating demand from $HEAT_{LT, SH}$ and $HEAT_{LT, HW}$ is distributed using $\%_{sh}(h, td)$, and partitioned into centralized and decentralized supply based on $\%_{DHN}(y)$. Public and private mobility end-uses are derived from Mobility Passenger and shaped by $\%_{pass}(h, td)$, with modal split determined by $\%_{Public}(y)$. Freight mobility uses Mobility Freight as its base, with time variation defined by $\%_{fr}(h, td)$ and distributed to rail, road, and boat according to $\%_{Fr,Rail}(y)$, $\%_{Fr,Road}(y)$, and $\%_{Fr,Boat}(y)$, respectively. In all relevant cases, $Net_{losses}(y, l, h, td)$ is included to account for network inefficiencies during energy delivery.

$$\mathrm{EndUses}(y,l,h,td) = \begin{cases} \frac{\mathrm{EndUses}(y,l)}{t_{op}} + \mathrm{EndUses}(y,\mathrm{LIGHTING}) \cdot \frac{\%\mathrm{elec}(h,td)}{t_{op}(h,td)} + \mathrm{Net}_{\mathrm{losses}}(y,l,h,td), & l = \mathrm{ELECTRICITY} \\ \left(\frac{\mathrm{EndUses}(y,\mathrm{HW})}{t_{op}} + \mathrm{EndUses}(y,\mathrm{SH}) \cdot \frac{\%\mathrm{sh}(h,td)}{t_{op}(h,td)}\right) \cdot \%\mathrm{Dhn}(y) + \mathrm{Net}_{\mathrm{losses}}(y,l,h,td), & l = \mathrm{HEAT}_{\mathrm{LowT,DHN}} \\ \left(\frac{\mathrm{EndUses}(y,\mathrm{HW})}{t_{op}} + \mathrm{EndUses}(y,\mathrm{SH}) \cdot \frac{\%\mathrm{sh}(h,td)}{t_{op}(h,td)}\right) \cdot (1 - \%\mathrm{Dhn}(y)), & l = \mathrm{HEAT}_{\mathrm{LowT,Decen}} \\ \mathrm{EndUses}(y,\mathrm{MobilityPassenger}) \cdot \frac{\%\mathrm{pass}(h,td)}{t_{op}(h,td)} \cdot \%\mathrm{Public}(y), & l = \mathrm{Mob}_{\mathrm{Public}} \\ \mathrm{EndUses}(y,\mathrm{MobilityPassenger}) \cdot \frac{\%\mathrm{pass}(h,td)}{t_{op}(h,td)} \cdot (1 - \%\mathrm{Public}(y)), & l = \mathrm{Mob}_{\mathrm{Private}} \\ \mathrm{EndUses}(y,\mathrm{MobilityFreight}) \cdot \frac{\%\mathrm{fr}(h,td)}{t_{op}(h,td)} \cdot \%\mathrm{Fr,Rail}(y), & l = \mathrm{Mob}_{\mathrm{FreightRail}} \\ \mathrm{EndUses}(y,\mathrm{MobilityFreight}) \cdot \frac{\%\mathrm{fr}(h,td)}{t_{op}(h,td)} \cdot \%\mathrm{Fr,Road}(y), & l = \mathrm{Mob}_{\mathrm{FreightRoad}} \\ \mathrm{EndUses}(y,\mathrm{MobilityFreight}) \cdot \frac{\%\mathrm{fr}(h,td)}{t_{op}(h,td)} \cdot \%\mathrm{Fr,Boat}(y), & l = \mathrm{Mob}_{\mathrm{FreightBoat}} \end{cases} \tag{24}$$

Additional constraints

This constraint enforces a flat nuclear generation profile across all hours and typical days within each modeled year. The hourly output F_t(y,NUCLEAR,h,td) is fixed to the constant annual nuclear generation level $P_{nuclear}$(y, representing baseload behavior of nuclear plants. This simplification reflects the technical and economic rationale for keeping nuclear production steady throughout the year.

$$F_t(y,\mathrm{NUCLEAR},h,td) = P_{\mathrm{nuclear}}(y) \quad \forall y \in \mathrm{YEARS},\ h \in \mathrm{HOURS},\ td \in \mathrm{TYPICAL\ DAYS} \tag{25}$$

Equations (26) and (27) establish a fixed operating strategy for technologies supplying passenger and freight mobility, respectively. For each passenger technology j, Eq. 26 allocates a constant share of total annual demand using $\%_{PassMob}$(y,j), applied uniformly across time based on the hourly time series $\%_{pass}(h, td)$. Similarly, Eq. 27 ensures that each freight transport technology j delivers a fixed portion of annual freight demand, defined by $\%_{FreightMob}$(y,j), and modulated over time using the distribution $\%_{fr}(h, td)$. These expressions avoid unrealistic inter-technology switching by enforcing consistent contributions across all hours and representative days.

$$F_t(y,j,h,td) = \%\mathrm{PassMob}(y,j) \cdot \left(\mathrm{EndUses}(y,\mathrm{MobilityPassenger}) \cdot \frac{\%\mathrm{pass}(h,td)}{t_{op}(h,td)}\right) \tag{26}$$

$$F_t(y,j,h,td) = \%\text{FreightMob}(y,j) \cdot \left(\text{EndUses}(y, \text{MobilityFreight}) \cdot \frac{\%\text{fr}(h,td)}{t_{\text{op}}(h,td)} \right) \tag{27}$$

$$\forall y \in \text{YEARS},\ j \in \text{TECH}_{\text{MobPass}},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Equation (28) ensures that the modal shares for freight transport—rail, road, and boat—are collectively exhaustive. The variables $\%_{\text{Fr,Rail}}(y)$, $\%_{\text{Fr,Road}}(y)$, and $\%_{\text{Fr,Boat}}(y)$ must sum to one in each year y, guaranteeing a complete allocation of freight demand across the three transport modes.

$$\%\text{Fr,Rail}(y) + \%\text{Fr,Road}(y) + \%\text{Fr,Boat}(y) = 1 \quad \forall y \in \text{YEARS} \tag{28}$$

Thermal solar and thermal storage constraints

The decentralised thermal solar output $F_{t,solar}(y, j, h, td)$ is constrained in Eq. (29) by the product of installed collector capacity $F_{solar}(y, j)$ and the hourly capacity factor cpt(y, DecSolar, h, td). This ensures that solar-based production does not exceed hourly resource availability. The condition applies to technologies j belonging to decentralized heating excluding DecSolar.

$$F_{t,solar}(y,j,h,td) \leq F_{solar}(y,j) \cdot c_{pt}(y, DecSolar, h, td) \tag{29}$$

$$\forall y \in \text{YEARS},\ j \in HeatLowTDec \setminus \{DecSolar\},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

The total decentralised solar capacity F(y, DecSolar) must at least match the sum of collector capacities $F_{solar}(y, j)$ across all technologies j in decentralized heating excluding DecSolar, as stated in Eq. (30). This condition guarantees consistency between the global solar infrastructure capacity and the shares allocated to each decentralised heating technology.

$$F(y, DecSolar) \geq \sum_{j \in HeatLowTDec \setminus \{DecSolar\}} F_{solar}(y,j) \quad \forall y \in \text{YEARS} \tag{30}$$

Decentralised heating technologies are required in Eq. (31) to supply their allocated share $\%_{\text{HeatDec}}(y, j)$ of low-temperature demand. The right-hand side uses EndUses(y, HW) and EndUses(y, SH), scaled by the time series $\%_{sh}(h, td)$ and normalised over top or top(h, td). The balance applies for all j in decentralized heating excluding DecSolar and i in $TS_{Dec}(j)$.

$$F_t(y,j,h,td) + F_{t,solar}(y,j,h,td) + \sum_{l \in \text{LAYERS}} [Sto_{out}(y,i,l,h,td) - Sto_{in}(y,i,l,h,td)] =$$

$$= \%\text{HeatDec}(y,j) \cdot \left(\frac{\text{EndUses}(y,HW)}{top} + \text{EndUses}(y,SH) \cdot \frac{\%\text{sh}(h,td)}{top(h,td)} \right) \tag{31}$$

$$\forall y \in \text{YEARS},\ j \in HeatLowTDec \setminus \{DecSolar\},\ i \in TSDec(j),\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Electric vehicles constraints

This equation connects the use of electric vehicles in V2G applications to their role as distributed energy storage units. It translates the presence of vehicles on the road into a quantifiable amount of battery capacity that can interact with the grid.

$$F(y,i) = \frac{F(y,j)}{veh_{capa}(y,j)} \cdot ev_{batt,size}(y,j) \tag{32}$$

$$\forall y \in \text{YEARS},\ j \in \text{V2G},\ i \in \text{EVs BATT OF V2G}(j)$$

The energy needs of each V2G vehicle are directly supported by its own battery. It captures the principle that batteries embedded in electric vehicles must first serve their associated mobility technologies before contributing to other services.

$$Sto_{out}(y,i,\text{Electricity},h,td) \geq -f(y,j,\text{Electricity}) \cdot Ft(y,j,h,td) \tag{33}$$

$$\forall y \in \text{YEARS},\ j \in \text{V2G},\ i \in \text{EVs BATT OF V2G}(j),\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Equation 34 maintains a minimum energy reserve within electric vehicle batteries throughout the day. It accounts for the practical reality that not all battery capacity is available at all times, ensuring mobility readiness is preserved.

$$Sto_{level}(y,i,t) \geq F(y,i) \cdot soc_{ev}(i,h) \tag{34}$$

$$\forall y \in \text{YEARS},\ j \in \text{V2G},\ i \in \text{EVs BATT OF V2G}(j),\ t \in \text{PERIODS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

Peak demand related constraints

This constraint ensures that decentralized heating technologies are sized to cover the highest levels of space heating demand observed during the year. It reflects the need for individual heating systems to operate reliably during extreme cold conditions, when demand reaches its peak.

$$F(y,j) \geq \text{peak}_{sh,factor} \cdot Ft(y,j,h,td) \tag{35}$$

$$\forall y \in \text{YEARS},\ j \in \text{TECH OF EUT(HeatLowTDec)} \setminus \{\text{DecSolar}\},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS}$$

This formulation identifies the peak heating demand in the district heating network. It serves as a prerequisite for infrastructure sizing, ensuring that the system design accounts for the most demanding moments in terms of heat delivery.

$$MaxHeatDemand(y) \geq EndUses(\text{HeatLowTDHN}, h, td)$$
$$\forall y \in \text{YEARS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS} \tag{36}$$

This condition guarantees that centralized heating technologies, together with their associated storage systems, are sufficient to meet the maximum heating needs of the district heating network. It enforces system adequacy during peak conditions by considering both direct production and stored heat that can be dispatched on demand.

$$\sum_{j \in \text{TECH OF EUT(HeatLowTDHN)}} F(y,j) + \sum_{i \in \text{STO OF EUT(HeatLowTDHN)}} \frac{F(y,i)}{tsto_{out}(y,i)} \geq$$
$$\geq \text{peak}_{sh,factor} \cdot MaxHeatDemand(y) \quad \forall y \in \text{YEARS} \tag{37}$$

Other constraints

To comply with annual decarbonization targets, the model constrains the yearly emissions $GWP_{tot}(y)$ to stay below a predefined limit $gwp_{limit}(y)$, as enforced in equation (38).

$$GWP_{tot}(y) \leq gwp_{limit}(y) \quad \forall y \in \text{YEARS} \tag{38}$$

Beyond annual limits, equation (39) ensures that the total accumulated greenhouse gas emissions over the transition period, represented by $GWP_{tot,transition}$, remain within the allowed carbon budget $gwp_{limit,transition}$.

$$GWP_{tot,transition} \leq gwp_{limit,transition} \tag{39}$$

The contribution of each technology j to a given energy layer eut is constrained through its share of output. Equation (40) ensures that the time-weighted operation $Ft(y, j, h, td) \cdot t_{op}(h, td)$ does not exceed a maximum fraction $f_{max,(\%)}(y, j)$ of the total output in that layer. Conversely, equation (41) guarantees that the same technology provides at least a minimum share, as defined by $f_{min,(\%)}(y, j)$. These conditions restrict the operational flexibility of the model to reflect diversification policies or technology preferences.

$$\sum_{t,h,td} Ft(y,j,h,td) \cdot t_{op}(h,td) \leq f_{max,\%}(y,j) \cdot \sum_{j',t,h,td} Ft(y,j',h,td) \cdot t_{op}(h,td) \tag{40}$$

$$\sum_{t,h,td} Ft(y,j,h,td) \cdot t_{op}(h,td) \geq f_{min,\%}(y,j) \cdot \sum_{j',t,h,td} Ft(y,j',h,td) \cdot t_{op}(h,td) \tag{41}$$

$$\forall y \in \text{YEARS},\ eut,\ j \in \text{TECH OF EUT}(eut)$$

Equation (42) fixes the capacity allocated to energy efficiency, F(y, Efficiency), to match the predefined trajectory efficiency(y), representing planned structural energy demand reductions.

$$F(y, \text{Efficiency}) = efficiency(y) \quad \forall\, y \in \text{YEARS} \tag{42}$$

To account for limitations in interconnection capacity, equation (43) restricts the electricity imported at each time step, Ft(y, Electricity, h, td), ensuring it does not exceed $elec_{import,max}(y)$ after multiplying by the respective time step duration $t_{op}(h, td)$.

$$\begin{gathered} Ft(y, \text{Electricity}, h, td) \cdot t_{op}(h, td) \leq elec_{import,max}(y) \\ \forall\, y \in \text{YEARS},\ h \in \text{HOURS},\ td \in \text{TYPICAL DAYS} \end{gathered} \tag{43}$$

Finally, equation (44) limits the deployment of solar technologies according to land availability. The surface required by F(y, PV), F(y, DecSolar), and F(y, DHNSolar) is computed based on power densities $powerd_{ensit}y_{,pv}$ and $powerdd_{ensit}y_{,solar\ thermal}$, and the total must stay within $solar_{area}(y)$.

$$\frac{F(y, \text{PV})}{power_{density,pv}} + \frac{F(y, \text{DecSolar}) + F(y, \text{DHNSolar})}{power_{density,solar\ thermal}} \leq solar_{area}(y) \quad \forall\, y \in \text{YEARS} \tag{44}$$

Constraints defining changes between temporal phases

The transition of installed capacity between two consecutive representative years is defined by equation (45). It updates the capacity $F(y_{stop}, i)$ based on the previous year's value $F(y_{start}, i)$, the new installations $F_{new}(p, i)$, the capacity reaching end-of-life $F_{old}(p, i)$, and any capacity prematurely dismantled $F_{decom}(p, p_2, i)$. This formulation ensures a consistent tracking of capacity evolution over time.

$$\begin{gathered} F(y_{stop}, i) = F(y_{start}, i) + F_{new}(p, i) - F_{old}(p, i) - \sum_{p_2} F_{decom}(p, p_2, i) \\ \forall\, p \in \text{PHASE},\ y_{start} \in \text{PHASE START}(p),\ y_{stop} \in \text{PHASE STOP}(p),\ i \in \text{TECHNOLOGIES} \end{gathered} \tag{45}$$

To prevent unrealistic decisions, equation (46) ensures that no decommissioning $F_{decom}(p_{decom}, p_{built}, i)$ is allowed when the phase of construction p_{built} is later than or equal to the phase of removal p_{decom}, unless explicitly permitted by $decom_{allowed}$. This maintains logical coherence in capacity changes.

$$\begin{gathered} F_{decom}(p_{decom}, p_{built}, i) = 0 \quad \text{if } decom_{allowed}(p_{decom}, p_{built}, i) = 0 \\ \forall\, p_{\text{decom}} \in \text{PHASE},\ p_{\text{built}} \in \text{PHASE} \cup \text{INITIAL PHASE},\ i \in \text{TECHNOLOGIES} \end{gathered} \tag{46}$$

To initialise the first phase of the pathway model, equation (47) sets the newly installed capacity F_{new} (p, i) equal to the installed capacity recorded in $YEAR_{2025}$. This provides a consistent starting point for transition modelling.

$$F_{new}(p_{\text{init}}, i) = F(y_{\text{init}}, i) \quad \forall\, i \in \text{TECHNOLOGIES} \tag{47}$$

The capacity reaching the end of its lifetime in a given phase is addressed in equation (48). If a technology is still in use, F_{old}(p, i) is zero. Otherwise, it is equal to the initial capacity installed F_{new}(age, i) minus any premature decommissioning that occurred before the end of its lifetime. This enables age-aware phase-out logic in the model.

$$F_{old}(p,i) = \begin{cases} 0 & \text{if } age = \text{STILL IN USE} \\ F_{new}(age,i) - \sum_{p_2} F_{decom}(p_2, age, i) & \text{otherwise} \end{cases} \tag{48}$$

$$\forall\, i \in \text{TECHNOLOGIES},\; p \in \text{PHASE},\; age \in \text{AGE}(i,p)$$

To ensure physical consistency, equation (49) enforces that a technology cannot be decommissioned if it was never built. This is done by requiring that the net remaining capacity (new installations minus total decommissioning) remains non-negative.

$$F_{new}(p,i) - \sum_{p_2} F_{decom}(p_2, p, i) \geq 0 \quad \forall\, i \in \text{TECHNOLOGIES},\; p \in \text{PHASE} \tag{49}$$

The following expression calculates the yearly energy output of technology j at the beginning of a phase. It is obtained by summing the hourly dispatch Ft(y_{start}, j, h, td), weighted by the time step duration t_{op}(h, td), across all hours and typical days. This value serves as the operational baseline to evaluate future technological changes.

$$F^{used}_{year,start}(y_{start}, j) = \sum_{t,h,td} Ft(y_{start}, j, h, td) \cdot t_{op}(h, td) \tag{50}$$

$$\forall\, p \in \text{PHASE},\; y_{start} \in \text{PHASE START}(p),\; j \in \text{TECHNOLOGIES}$$

To track technological transitions between two consecutive representative years, the variable Δ_{change}(p, j) quantifies the change in the energy supplied by technology j over phase p. It is constrained to be greater than or equal to the decrease in annual energy output from y_{start} to y_{stop}. This ensures that all reductions in activity are explicitly captured as measurable transitions.

$$\Delta_{change}(p,j) \geq \sum_{t,h,td} Ft(y_{start}, j, h, td) \cdot t_{op}(h,td) - \sum_{t,h,td} Ft(y_{stop}, j, h, td) \cdot t_{op}(h,td) \tag{51}$$

$$\forall\, p \in \text{PHASE},\; y_{start} \in Y_{START}(p),\; y_{stop} \in Y_{STOP}(p),\; j \in \text{TECHNOLOGIES}$$

To maintain realism in sectoral evolution, the model places upper bounds on total allowed change in specific domains. For low-temperature heat, the sum of Δ{change}(p, j) across all technologies j within the category HeatLowT must not exceed a fraction limit renovation}+ of the total annual heat demand at y_{start}. Similarly, the total changes in technologies for passenger and freight mobility are bounded by $limit_{pass,mob,changes}$ and $limit_{freight,changes}$, respectively, each scaled by the corresponding annual end-use demand at the start of the phase. These constraints represent inertia in societal and infrastructure adaptation across sectors.

$$\sum_{\substack{euc \in \text{EUT OF CAT(HeatLowT)} \\ j \in \text{TECH OF EUT}(euc)}} \Delta_{change}(p, j) \leq limit_{LT,renovation} \cdot (enduses_{input}(y_{start}, \text{HotWater}) + enduses_{input}(y_{start}, \text{SpaceHeat}))$$

$$\sum_{\substack{euc \in \text{EUT OF CAT(MobPass)} \\ j \in \text{TECH OF EUT}(euc)}} \Delta_{change}(p, j) \leq limit_{pass,mob,changes} \cdot enduses_{input}(y_{start}, \text{MobPass})$$

$$\sum_{\substack{euc \in \text{EUT OF CAT(MobFreight)} \\ j \in \text{TECH OF EUT}(euc)}} \Delta_{change}(p, j) \leq limit_{freight,changes} \cdot enduses_{input}(y_{start}, \text{MobFreight})$$

(51,52,53)

Alternative cost definitions

The total capital expenditure for the transition (CAPEX), is calculated as the sum of all phase-level investments $C_{inv,phase}(p)$, from which the residual value of unused investments $C_{inv,return}(i)$ is subtracted. This ensures that only the effective cost of long-term investments is considered.

$$C_{tot,capex} = \sum_{p \in \text{PHASE}} C_{inv,phase}(p) - \sum_{i \in \text{TECHNOLOGIES}} C_{inv,return}(i) \tag{54}$$

$C_{inv,phase}$ (p) captures the total investment cost for a given phase p. It is computed by multiplying the newly installed capacity F_{new}(p, i) by the average of the technology-specific investment costs from the start and end of the phase, scaled by the annualisation factor τ_{phase}(p).

$$C_{inv,phase}(p) = \sum_{i \in \text{TECHNOLOGIES}} F_{new}(p, i) \cdot \tau_{phase}(p) \cdot \frac{c_{inv}(y_{start}, i) + c_{inv}(y_{stop}, i)}{2} \tag{55}$$

$$\forall\, p \in \text{PHASE},\ y_{start} \in \text{PHASE START}(p),\ y_{stop} \in \text{PHASE STOP}(p)$$

$C_{inv,phase,tech}$(p, i) follows the same logic as $C_{inv,phase}$ (p) but at the level of individual technologies. It tracks the specific investment attributed to each technology over the phase.

$$C_{inv,phase,tech}(p, i) = F_{new}(p, i) \cdot \tau_{phase}(p) \cdot \frac{c_{inv}(y_{start}, i) + c_{inv}(y_{stop}, i)}{2} \tag{56}$$

$$\forall\, p \in \text{PHASE},\ y_{start} \in \text{PHASE START}(p),\ y_{stop} \in \text{PHASE STOP}(p),\ i \in \text{TECHNOLOGIES}$$

$C_{inv,return}(i)$ represents the portion of a technology's investment that remains unused due to early decommissioning or lifetime not fully reached within the transition horizon. This value is deducted from total capital costs to avoid overestimating long-term investment expenses.

$$C_{inv,return}(i) = \sum_{\substack{p \in \text{PHASE}, \\ y_{start} \in \text{PHASE START}(p), \\ y_{stop} \in \text{PHASE STOP}(p)}} \left(\frac{remaining_{years}(i,p)}{lifetime(y_{start}, i)} \cdot \left(F_{new}(p,i) - \right. \right.$$
$$\left. \left. - \sum_{p_2 \in \text{PHASE}} F_{decom}(p_2, p, i) \right) \cdot \tau_{phase}(p) \cdot \frac{c_{inv}(y_{start}, i) + c_{inv}(y_{stop}, i)}{2} \right) \tag{57}$$

$C_{tot,opex}$ reflects the total operating cost across the entire transition. It includes the baseline operating cost at the initial year and the accumulated costs over all phases, calculated using the average operating cost at the start and end years of each phase and adjusted by the annualization factor and phase duration.

$$C_{tot,opex} = C_{opex}(y = \text{YEAR}_{start}) + t_{phase} \cdot \sum_{\substack{p \in \text{PHASE}, \\ y_{start} \in \text{PHASE START}(p), \\ y_{stop} \in \text{PHASE STOP}(p)}} \left(\frac{C_{opex}(y_{start}) + C_{opex}(y_{stop})}{2} \cdot \tau_{phase}(p) \right) \tag{58}$$

$C_{opex}(y)$ aggregates the annual operating cost for a given year y. It sums the maintenance costs of all technologies and the resource consumption costs during that year.

$$C_{opex}(y) = \sum_{j \in \text{TECHNOLOGIES}} C_{maint}(y, j) + \sum_{i \in \text{RESOURCES}} C_{op}(y, i) \quad \forall y \in \text{YEARS} \tag{59}$$

$C_{op,phase,tech}(p, i)$ estimates the phase-level operating cost for each technology. It averages the annual maintenance costs across the phase duration and scales it by the phase duration and annualisation factor.

$$C_{op,phase,tech}(p,i) = t_{phase} \cdot \left(\frac{C_{maint}(y_{start}, i) + C_{maint}(y_{stop}, i)}{2} \cdot \tau_{phase}(p) \right) \quad \forall p \in \text{PHASE}, \; i \in \text{TECHNOLOGIES} \tag{60}$$

$C_{op,phase,res}(p, i)$ estimates the resource-related operational cost during a phase. It is based on the average of resource-specific operation costs at the start and end years of the phase.

$$C_{op,phase,res}(p,i) = t_{phase} \cdot \left(\frac{C_{op}(y_{start}, i) + C_{op}(y_{stop}, i)}{2} \cdot \tau_{phase}(p) \right) \quad \forall p \in \text{PHASE}, \; i \in \text{RESOURCES} \tag{61}$$

This constraint places an upper limit on the investment that can occur within each phase, defined by $max_{inv,phase}(p)$. It ensures investment levels remain realistic and manageable year by year.

$$C_{inv,phase}(p) \leq max_{inv,phase}(p) \quad \forall p \in \text{PHASE} \tag{62}$$

Objective functions

In the context of energy system optimization, the objective function can be formulated in various ways depending on the specific goals of the analysis. Different formulations may prioritize economic cost minimization, emissions reduction, or a combination of both. The choice of objective reflects the strategic orientation of the model, whether it aims to design a cost-efficient pathway, a low-carbon transition, or a balanced trade-off between multiple performance indicators. In the case of EnergyScope Pathway is selected minimizing only the economic costs of the system (investment and operation). It is used when the goal is to find the least-cost energy transition, without directly accounting for environmental impacts.

$$\min \quad C_{tot,capex} + C_{tot,opex} \tag{63}$$

In this case the emissions are not characterized in the objective function since they are limited through the parameters GWP_{budget} and $GWP_{limit.}$

3.3 Environment for the implementation

The implementation of the EnergyScope Pathway model combines the use of AMPL with Python to simulate long-term energy transitions. AMPL is used as the core modeling language due to its clear and concise structure for defining large-scale linear programming problems. It is particularly well-suited for expressing the model's optimization structure and system-wide constraints.

To complement AMPL, the model is run through an environment created with Anaconda using Python version 3.7.6. Within this setup, the amplpy library is installed, allowing Python to launch AMPL simulations and exchange data. Python scripts are used to define high-level parameters, such as the total GWP limit over the transition, the emission target for the final year, and the simulation horizon. These parameters are processed into files that AMPL reads to solve the optimization problem.

The model's directory is organized in a modular way. In the ESMY folder, see below, the typical day selection model is located in the STEP_1_TD_selection folder, while the full energy system optimization across multiple years is implemented in STEP_2_Energy_Model. These stages are supported by a general data management folder and documentation files. A schematic of this directory structure is shown in the figures provided. This setup ensures a clear workflow from data preparation to optimization and result analysis.

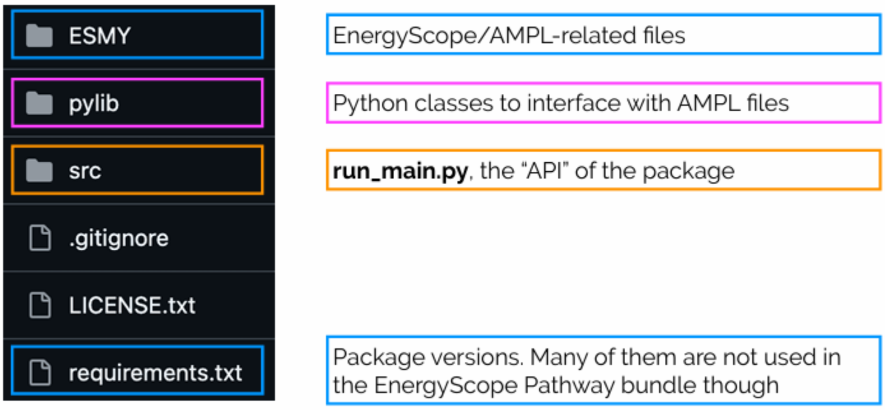

Figure 3.8 – Main directory of ES Pathway

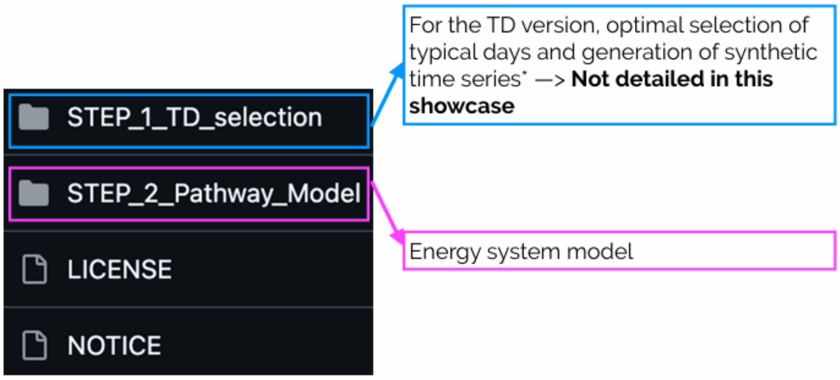

Figure 3.9 – Content in ESMY folder (Main directory>ESMY)

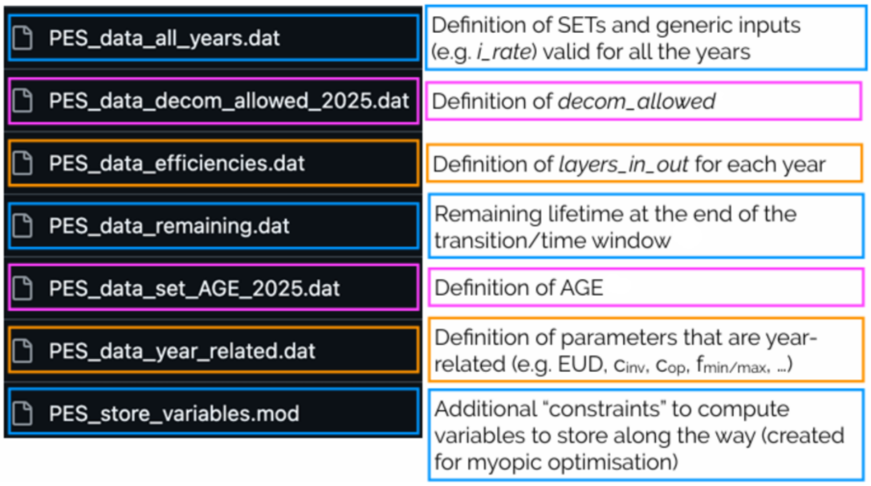

Figure 3.10– General ES Pathway files (Main directory>ESMY>STEP_2_Pathwaw_Model)

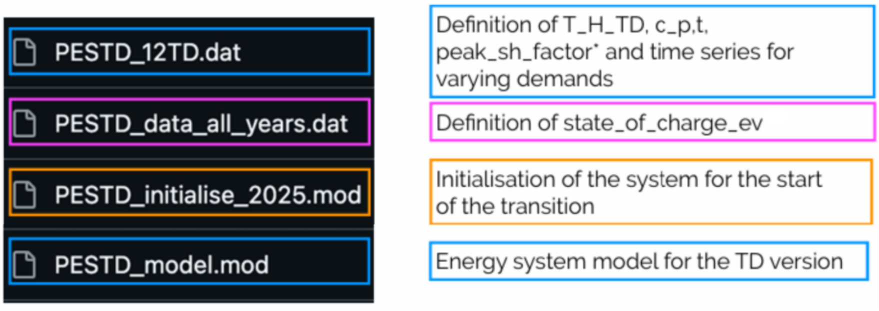

Figure 3.11 – Specific files for ES Pathway TD (Main directory>ESMY>STEP_2_Pathwaw_Model)

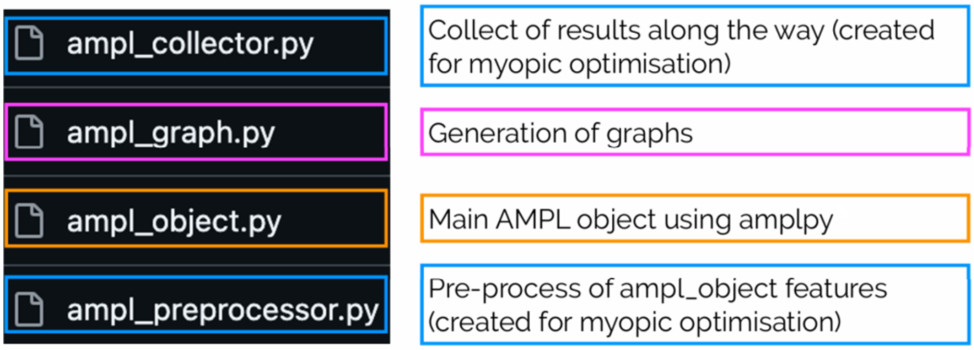

Figure 3.12 – Specific python classes (Main directory>pylib)

4. Italian case studty

Developing realistic and effective energy transition strategies requires more than just powerful modelling tools: it depends on a deep and accurate understanding of the system being studied. Each national energy system has its own structure, constraints and opportunities, shaped by geography, infrastructure, resource availability, government policies and socio-economic aspects. For an optimization model to generate meaningful and actionable insights, it must be applied to a well-characterized context, one that reflects the real-world interactions between supply, conversion, infrastructure, and end-use sectors. Italy offers a particularly rich and complex example of such a system, making it an ideal case for long-term whole-energy system planning.

Italy's current energy landscape combines mature infrastructure and increasing renewable penetration with persistent structural dependencies. While the country has made significant progress in solar deployment and energy efficiency over the past decade, it remains highly reliant on imported fossil fuels, particularly natural gas, which still represents more than 40% of total energy supply. Electricity and gas networks are well interconnected both internally and with bordering countries, enabling some flexibility in balancing supply and demand. However, the national energy system also faces major challenges such as the need to decarbonize sectors like transport and industry that still rely heavily on fossil inputs.

The aim of this chapter is to apply the EnergyScope Pathway model to the Italian context in order to explore credible decarbonization strategies that combine technological feasibility, resource constraints, and system-level integration. The model includes the entire energy chain: domestic and imported resources, conversion technologies, storage, and final energy services for electricity, heating, mobility, and industrial needs.

A key premise of this modelling effort is that high-quality optimization results can only be achieved if the energy system is described with sufficient clarity and granularity. This includes both a sound understanding of existing infrastructure and a realistic projection of future evolutions in technologies, prices, efficiencies, and demand patterns. Each element of the system must be placed within a consistent structure to produce results that are technically meaningful and replicable into the real world.

To that end, this work builds upon the comprehensive dataset developed by Borasio and Moret (2022), who implemented the EnergyScope TD model for Italy [14]. Their open-source framework has been carefully adapted and extended here for use within the EnergyScope Pathway formulation, with updated assumptions and scenario parameters aligned to the 2025–2050 horizon. Additionally, the structure and methodological principles follow the modelling approach developed by Gauthier Limpens [54], who contributed to the design and validation of EnergyScope Pathway in earlier studies based on Belgium.

The sections that follow describe the composition of the Italian energy system as implemented in the model, detail the data sources and scenario assumptions used, and present the modelling framework applied to evaluate transition strategies toward a deeply decarbonized future.

4.1 Typical days

As described in Section 3.1, the EnergyScope Pathway model adopts a time-reduction strategy based on the use of typical days (TDs). Instead of representing all 365 days of the year in detail, a limited set of representative days is selected using clustering techniques. These typical days are designed to capture the essential variability of key time series, such as electricity demand, heating needs, solar and wind availability, across the year. This allows the model to approximate seasonal and daily dynamics while keeping computational time manageable.

For the Italian case study, 12 typical days were used. This number represents a good compromise between temporal representation and model tractability, as discussed and validated in previous applications of the model. The clustering method applied is the same as the one used in the original EnergyScope TD study by Borasio and Moret [14]. Specifically, we rely on the methodology originally proposed by Domínguez-Muñoz et al. [62], as implemented by Borasio for Italy. As a result, the exact same typical days used in that study have been adopted here without modification, ensuring perfect consistency in temporal modelling between EnergyScope TD and EnergyScope Pathway for Italy.

The figure below (Figure 4.1) shows the distribution of the 12 typical days across the full year. Each point represents a real calendar day and its corresponding assigned TD. The allocation reveals clear seasonal patterns, with winter, summer, and mid-season periods well represented across the selected days. This temporal structure plays a crucial role in capturing how renewable generation and energy demand shift throughout the year.

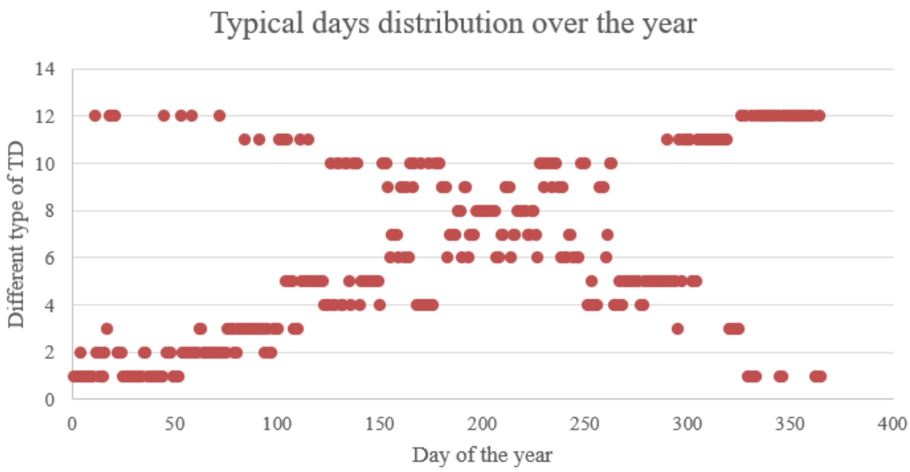

Figure 4.1 – Typical days representation

This figure is conceptually analogous to the one used in the Belgian case study presented by Limpens [54]. While the geographical context differs, the methodological framework is identical. In both cases, the TD selection is based on clustering key demand and supply time series with equal weighting, ensuring that both sides of the energy system are adequately captured. The approach allows the model to simulate system operation under realistic temporal conditions, while dramatically reducing the number of steps involved in the optimization.

For the definition of the typical days, production and demand profiles of all the days within a year are provided. Then, through the method previously explained in chapter 3, twelve days are selected as typical days depending on their similarity.

The time series used in this study includes the electricity demand across all sectors, which captures daily and seasonal fluctuations among winter and summer, as well as the heating demand, which is highly seasonal and dominated by winter space heating needs. Passenger and freight mobility is also included and show stable demand across time, though there is some hourly variation in the passenger mobility.

In addition to these demand profiles, the model also uses detailed hourly time series for renewable energy availability, referred to as c_p_t. Time series contains the hourly capacity factors for photovoltaic, onshore wind, offshore wind, decentralized solar thermal, DHN solar thermal, as well as the two hydropower sources: river hydro and hydro dams. These profiles reflect the weather-dependent and geographically specific nature of renewable generation and are essential to capture the intermittency and complementarity of renewable supply throughout the year.

Adapting all of these time series to match the typical day structure ensures that the temporal dynamics of the Italian energy system are adequately represented in the model. This step is essential to produce realistic system designs that respond properly to both peak demands and the fluctuating nature of renewable resources.

4.2 End use demand

In the EnergyScope Pathway model, a key distinction is made between Final Energy Consumption (FEC) and End-Use Demand (EUD). While FEC refers to the energy delivered to the consumer, EUD focuses on the useful energy actually needed to provide a service, such as heat or mobility. This approach allows the model to represent energy needs more accurately and independently of the technologies used. This distinction is one of the core strengths of EnergyScope Pathway, enabling a technology-neutral and service-oriented optimization of the energy system.

In this study, the Italian end-use energy demand (EUD) has been structured around four main final demand sectors: households, services, industry, and transport. Each of these sectors can be associated with one or more of the following energy services: electricity, low-temperature heat (mainly for space heating, water heating and cooking), high-temperature heat (primarily for industrial processes), and mobility (subdivided into passenger transport, both private and public, and freight transport).

The annual energy demands for each sector and energy service were obtained from the open dataset provided by ETM (Energy Transition Model) [55], were the Italian energy system model is properly define. This source provides long-term demand trajectories up to 2050, including expected evolutions in electrification and sectoral activity. The demand projections reflect current policy commitments, expected efficiency gains, and technological developments across the sectors.

Each energy service is assigned to one or more sectors as follows:

- **Households**: demand for electricity and low-temperature heat, mainly related to space heating, domestic hot water, cooking, and the use of household appliances.
- **Services**: demand for electricity and low-temperature heat, especially for space heating and lighting in commercial buildings, offices, and public facilities.
- **Industry**: demand for electricity, low-temperature heat and high-temperature heat. Industrial processes are typically the main source of high-temperature heat demand.
- **Transport**: demand for passenger and freight mobility, with subcategories for different transport modes (electric, fuel-based, public, private, etc.).

While in previous modelling work by Borasio and Moret [14] a specific demand category for cooling (space and process refrigeration) was considered separately, in this study that demand has been included within the electricity demand. This simplification is based on the assumption that nearly all cooling technologies operate using electricity, and therefore the associated energy input is already captured within the overall electricity consumption projections. This decision helps reduce redundancy in the model structure while preserving the accuracy of energy balances.

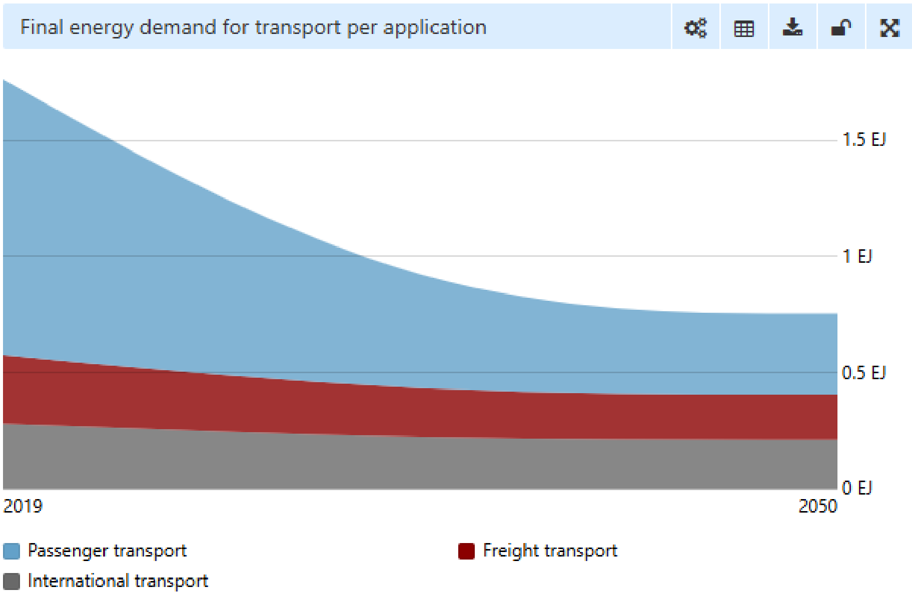

Figure 4.2 – Projected energy demand for transportation

As we can see in the figures 4.2 and 4.3 taken from the data source, the total energy demand in Italy is expected to decrease over the coming decades. This reduction is primarily driven by improvements in energy intensity, defined as the amount of energy required to produce one unit of economic output (e.g., per euro of GDP). As sectors become more efficient, through better thermal insulation in buildings, more efficient machinery, advanced process design, or digital energy management, less energy is needed to sustain economic activity. Other assumptions can be made out of the decreasing EUDs, such as demography variation or change in the consumer mentality towards a more responsible use of energy.

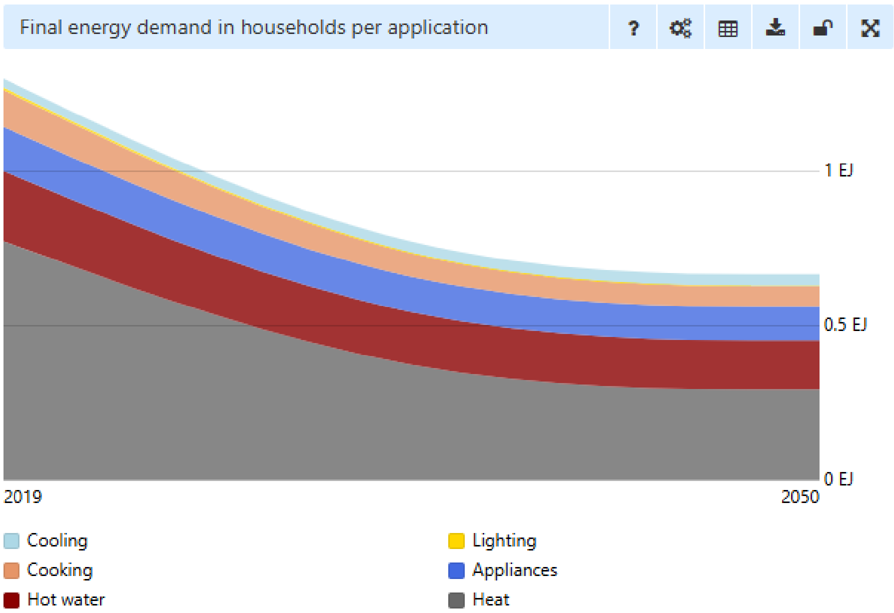

Figure 4.3 – Projected energy demand for households

Electricity is the notable exception to this overall downward trend. While most energy vectors (such as fossil fuels used for heating and transport) are projected to decline in absolute terms, electricity demand is expected to increase, becoming the dominant energy carrier. This trend is a direct consequence of the strategic role that electrification plays in energy transition. Technologies such as heat pumps, electric vehicles, and electric industrial processes not only offer higher efficiency but also enable the use of decarbonized power, especially as renewable electricity becomes more prevalent in the supply mix.

Overall, the demand data used in this study reflects a balanced and realistic trajectory for Italy's decarbonization pathway: decreasing total energy consumption thanks to improved efficiency and energy intensity, accompanied by a gradual but significant shift towards electricity as the backbone of the future low-carbon energy system.

4.3 Resources

In the model, all energy resources are classified by two criteria: their origin, either endogenous (produced within Italy) or exogenous (imported), and their type, either renewable or non-renewable. This last classification is consistent with the internal definitions of EnergyScope Pathway and is essential for properly representing supply options, constraints, and environmental impacts.

The set of resources considered includes conventional fuels such as gasoline, diesel, light fuel oil (LFO), natural gas, and coal, alongside cleaner or renewable alternatives like bioethanol, biodiesel, renewable gas (GAS_RE), wood, and wet biomass. Advanced synthetic carriers such as hydrogen (H_2), ammonia, and methanol are also included, both in their fossil-based and renewable forms (e.g. H_2_RE, AMMONIA_RE, METHANOL_RE). However, availability for the previous resources in their non-renewable form are set to 0. This is because they are currently mainly used un the non-energy sector, which is not included in the scope of this study. If the model requires some of these fuels for the energy sector, they will be synthetically produced in Italy, or limitedly imported from the exterior. In addition, the model considers electricity imports/exports (which mainly accounts for the electricity consumed in Italy and produced outside its borders, usually from France or Switzerland. Municipal waste and biomass is not treated as a fully renewable source due to its mixed biogenic content.

Some resources, such as biofuels (bioethanol, biodiesel and gas, ammonia, methanol and hydrogen in their renewable form) wood, or renewable gas, can either be produced domestically or imported, depending on techno-economic feasibility. Specifically, renewable ammonia and hydrogen are assumed as imported. While all renewable gas availability is produced within the borders of the county.

The model also includes direct renewable energy potentials for wind (RES_WIND), solar (RES_SOLAR), hydropower (RES_HYDRO), and geothermal energy (RES_GEO). These are not energy carriers themselves, but rather inputs for conversion technologies (e.g. wind turbines or PV panels), and their availability determines how much electricity or heat can be generated from local renewable sources.

In parallel, the model tracks carbon flows through dedicated carbon dioxide resources: CO2_ATM (carbon from the atmosphere), CO2_INDUSTRY (from industrial processes), CO2_CAPTURED (captured emissions), and CO2_EMISSIONS (final release to the atmosphere). These variables enable the integration of carbon capture and synthetic fuel production processes into the optimization.

Each resource in the model is defined by three main attributes:

- **availability**: the maximum amount of that resource that can be used per year. For endogenous resources, this refers to their technical or sustainable potential; for imported resources, it reflects infrastructure or market constraints.
- $\mathbf{c_{op}}$: the operational cost of using the resource, mainly expressed in €/GWh. It includes the purchase cost and, where relevant, transport or handling costs. This does not cover capital expenditures on conversion technologies.
- $\mathbf{gwp_{op}}$: the operational global warming potential, mainly measured in ktCO$_2$-eq/GWh. It accounts for all emissions linked to extraction, processing, transport, and use of the resource, based on life-cycle assessment standards.

These attributes are central to the optimization logic of the model, as they define the trade-offs between cost, emissions, and resource accessibility. The numerical values used for these parameters are based on the data developed in the EnergyScope TD implementation for Italy by Borasio and Moret, updated and adapted where necessary to fit the current EnergyScope Pathway formulation and timeframe.

Some of the data, mainly availability, were extracted from the data-base of the university research group under which this project was conducted. This is the case for the availability of biodiesel, wood, waste, among others. Also is worth mentioning that renewable energy potentials (e.g. RES_SOLAR, RES_WIND, RES_GEO…) is set as unlimited since the extracting energy out of them relies mainly on their respective installed capacities.

As stated before, a key resource such as electricity is also eligible to import from the exterior. This is why, after studying the Italian historical electricity exchange from the International Energy Agency [56], the maximum import of electricity throughout all the years is set to the 20% of all the electricity demand of the country.

Land for renewable development of solar technologies (PV, solar thermal) is also limited. In this study is assumed at 1% of the total Italian surface extension.

4.4 Technologies

The transition toward a low-carbon energy system relies fundamentally on the availability, performance, and cost evolution of energy technologies. As the energy system transforms over the coming decades, the role of technology will evolve. Some technologies, particularly those based on renewable sources or electrification, are expected to become more efficient, more affordable, and more widely deployed. Others, such as fossil-based systems, may become less competitive due to environmental regulation, depletion of accessible reserves, or social acceptability. For this reason, the proper definition of technological parameters is a crucial step in any optimization model that aims to support long-term energy planning.

In this study, each technology is described using a set of techno-economic indicators, including efficiency, operational cost, investment cost, and greenhouse gas emissions, as well as the efficiency of those that transform or storage energy. These indicators determine how the system balances energy flow, manages emissions, and allocates investments. The data introduced here are integrated into the EnergyScope Pathway model and serve as fixed input parameters, not subject to optimization, so their accuracy and consistency are essential to produce meaningful results. Description of the values used and key figures will be detailed in the next sections of this chapter.

The technological dataset used for this work builds primarily on the open-source EnergyScope TD model for Italy developed by Borasio and Moret. That study offers a structured and well-referenced collection of techno-economic values adapted to the Italian energy system and has been a core reference for this project. The data has been carefully transferred and adjusted to match the format and structure required by the EnergyScope Pathway framework, which allows for greater flexibility in time and technology representation.

To reflect changes over time in performance and cost, the evolution trajectories of the technologies were modelled following the methodology proposed by Gaultier Limpens in his application of EnergyScope Pathway to the Belgian case [54]. His work provides a coherent set of assumptions for how technologies are expected to develop at the European level, based on current trends, learning curves, and EU policy targets. Given the shared context of Italy and Belgium within the EU energy and innovation landscape, it is considered reasonable to assume similar trajectories for both countries.

In particular, the focus of the present study is placed on the most relevant energy conversion and storage technologies, which act as the cornerstone of the energy system. These include systems such as combined-cycle gas turbines (CCGT) for electricity generation, photovoltaic panels (PV) for solar power, pump hydro storage and dams, battery storage, thermal boilers for heat generation, among others. These technologies enable the transformation of primary resources into usable energy carriers, the balancing of supply and demand over time, and the integration of variable renewables into the energy mix.

Each of these technologies has been included in the model with its specific performance characteristics and cost structure. In the following sections, we present an overview of the assumed techno-economic data, the rationale behind each value, and the sources used to justify these choices.

It is also important to highlight that, although the technology set used in this study is largely based on the structure inherited from previous EnergyScope applications, one additional technology had to be introduced specifically for the Italian context: hydro_dam. In the original Belgian model, this technology was not considered due to its very limited contribution to national electricity production. However, in Italy, dam hydropower plays a central role in the renewable energy mix and remains one of the country’s most important sources of dispatchable renewable electricity. For this reason, the model was adapted to explicitly include hydro_dam, with dedicated techno-economic parameters and capacity constraints, in order to accurately represent its contribution to the national energy system.

4.4.1 Data that must be adapted

For a model to represent an energy system in a way that is both realistic and computationally manageable, it is not sufficient to define resources and energy demands alone, as done in section 4.3. It is also necessary to introduce technical limits on how much of each technology can be deployed. These constraints reflect physical, economic, political, and spatial boundaries, and are expressed in the model through the parameters f_{min} and f_{max}, which define the minimum and maximum installed capacity allowed for each conversion technology.

While the core of the EnergyScope optimization process is to determine the most cost-effective and low-emission mix of technologies, this optimization must operate within a predefined and credible range of possibilities. In this sense, the f_{max} and f_{min} values play a double role. On one hand, they preserve flexibility by not forcing unnecessary restrictions. On the other, they are essential to avoid unrealistic outcomes, such as the massive expansion of outdated or already-maximised technologies, or the disappearance of technologies that must remain in operation for system stability.

The majority of these capacity bounds were taken directly from the EnergyScope TD dataset for Italy developed by Borasio and Moret. Their work provides a consistent and well-documented reference point for technology availability across the Italian system. However, for certain key electricity-generating technologies, updated information was included from additional sources to better reflect the present situation and most recent trends in deployment.

Specifically, the installed capacity for combined-cycle gas turbines (CCGT) was updated based on technical data from one of Italy's main plants [57, 58], while the deployment levels of photovoltaics were updated with the latest figures from national reports that reflect the country's growing solar capacity [59]. Likewise, updated capacity estimates for onshore and offshore wind were taken from a recent European-wide outlook study [60], and data for geothermal energy came from a comprehensive technical review of existing installations and long-term potential in Italy[61]. These references were used to set informed f_{max} values, ensuring that the model does not overestimate the deployable potential of each technology.

In contrast, for technologies with high greenhouse gas emissions, such as coal-fired power generation, a policy-based limit was applied: beginning in 2030, their maximum capacity was set to zero. This constraint reflects Italy's and the EU's broader decarbonization strategy and ensures that the model does not rely on carbon-intensive technologies that are expected to be phased out soon. Additionally and according to the Italian energy system, all capacities regarding nuclear power are set to null since there is no participation of nuclear technologies in the Italian energy mix. However, as explained further in this document, scenarios analysis will be made and nuclear power will be taken into consideration.

In parallel to capacity constraints, it is also necessary to define spatial constraints, particularly for land-intensive technologies like solar energy. To account for this, the model includes the parameters $power\_density_{PV}$ and $power\_density_{solar\ thermal}$, which define the amount of electrical or thermal power that can be installed per unit of land area [GWh/km^2]. These parameters are critical to estimate the surface required to deploy utility-scale solar technologies, and to ensure that system configurations remain spatially feasible. Without them, the model could, for example, install impractically large solar capacities without considering real-world land limitations.

The values of $power\_density_{pv}$ and $power\_density_{solar\ thermal}$ used in this study are calculated based on the methodology described in Limpens' thesis [54], where power density depends on the efficiency of the technology, the average solar irradiation received, and its typical capacity factor. This formulation allows for an accurate translation of solar potential into land use requirements, while keeping the model consistent with physical and climatic conditions.

By combining all these elements, capacity limits, policy constraints, and spatial parameters, the model is able to define a feasible and coherent solution space. This makes it possible for the optimization to explore viable decarbonization strategies that are grounded in technical reality and consistent with national and European energy transition goals. Despite now having the most important inputs adapted for our case study, given the similarity in many aspects between Belgium and Italy, further adaptations can be done to further represent the Italian case study. In the next chapter said adaptation are introduced.

4.4.2 Data that can be adapted

Some of the technologies included in the model have been adapted specifically for the Italian context. This approach follows the methodology presented by Xavier Rixhon [13] during an EnergyScope Pathway Community event, where he explained how to transfer the model originally developed for Belgium to other national energy systems. According to that method, some parameters must be adapted, as detailed in the previous sections—while others may remain unchanged, depending on the similarity between the original and the target system. In this study, most of the data was carefully adapted to reflect Italian conditions, but a few parameters were maintained unchanged when no significant differences were found or when the original assumptions remained valid.

General data

In order to make the model more realistic, several structural parameters beyond resource and technology definitions were also modified. Among them, the discount rate was adjusted to better reflect Italy’s macroeconomic context and investment risk profile. In parallel, the shares of supply within sectors were adapted, to impose minimum and maximum bounds on how different technologies or modes contribute within specific subsectors. For instance, $\%mobility_{public}(min/max)$ sets the bounds for the contribution of public transport within total passenger mobility, while the share for private mobility is automatically defined given that public and private make up for the hole passenger mobility. While $\%freight_{train}(min/max)$, and $\%freight_{road}$ (min/max) define modal shares for freight transport. Similarly, %heatDHN(min/max) constrains the use of district heating in the overall heat supply. All models have been adjusted to Borasio work and ETM[55].

Additionally, particular attention was given to the annual GWP (global warming potential) limits, which were defined for each key milestone year in the simulation: 2025, 2030, 2035, 2040, 2045, and 2050. The starting point was the level of territorial emissions recorded in Italy for the year 2025. From there, the 2030 limit was calculated in line with the European Green Deal target [5], which calls for a 55% reduction in emissions compared to 1990 levels. For the remaining milestone years, the emissions limits were linearly interpolated down to a final target of 20,000 $ktCO_2$-eq by 2050, a value aligned with the EU’s Net-Zero emission target for said year. This progressive carbon cap ensures that the standardized stays on track with both European and national climate objectives, while still allowing flexibility in how the system evolves over time.

The model also incorporates parameters that account for social inertia, the limitations on how quickly society can adapt to technological shifts or behavioural changes across transition periods. These are represented by variables such as $limit_{LT,renovation}$, $limit_{pass,mob,changes}$, and $limit_{freight,changes}$, which constrain the maximum variation in technology adoption or usage share between two consecutive simulation periods. In the original configuration, the model allowed for changes of up to 33% per phase for low-temperature (LT) technologies and 50% for mobility-related technologies. However, in this study, these values have been reduced uniformly to 25% for all three cases, based on the assumption that societal and infrastructural transformation is generally slower and more constrained than what those upper bounds would imply. The revised limits reflect the assumption that it is not realistic to change half of the vehicles or trucks in use within just five years. Reducing the allowed change to a maximum of 25% per period ensures that the model reflects more gradual and plausible transitions in the mobility and heating sectors. No investment limits have been applied to the model since minimizing the cost is one of the main objectives of the optimization. Total freedom is given to the model to choose the CAPEX expenditure as long as it is aligned with the other constraints.

Finally, the transmission and distribution losses for both electricity and district heating networks were also adapted. The values used in this study are based on those previously defined by Borasio and Moret in their EnergyScope TD model for Italy, and reflect realistic technical losses under current infrastructure conditions. The cost if extending the electricity distribution grid due to electrification has also been updated according to previous literature.

Technology costs

Another essential aspect of modelling the energy system transition lies in how technology costs evolve over time. In this study, both investment costs (c_inv) and maintenance costs (c_maint) are defined for each technology and adjusted across milestone years between 2025 and 2050. These cost trajectories influence the standardized process by guiding the model towards the most economically viable technological configurations.

The evolutionary trends applied to these costs are based on the methodology originally developed by Gaultier Limpens [54] in his doctoral study on the Belgian energy system, where cost variations over time were estimated using learning curves and policy assumptions for a broad range of energy technologies. For the present study, these trends have been adapted to the Italian context by recalibrating them using the techno-economic baseline data collected by Borasio and Moret [14] in their implementation of the EnergyScope TD model for Italy. This hybrid approach ensures that the relative evolution of each technology remains consistent with broader European trends, while the absolute cost levels are grounded in Italy-specific data.

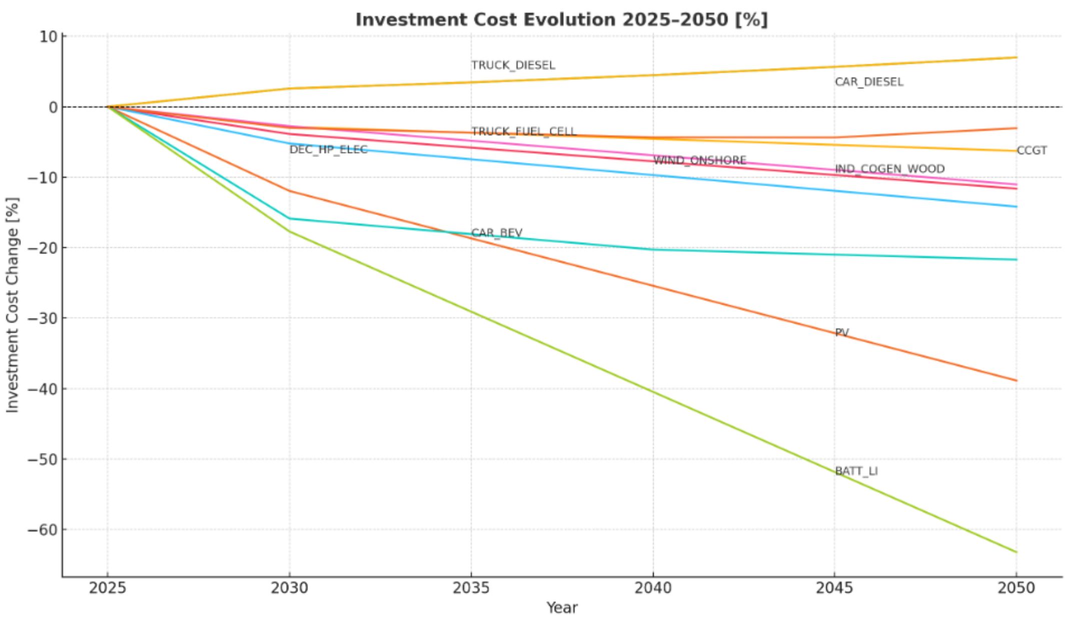

Figure 4.4 – Estimation of investment cost tendencies

Technologies do not evolve uniformly. Mature technologies, such as combined-cycle gas turbines (CCGT), industrial cogeneration systems, or district heating installations, already benefit from well-established industrial processes and economies of scale. As such, they exhibit only slight cost reductions over time. These improvements are often limited to incremental gains in efficiency, standardization, or materials.

By contrast, emerging technologies, including solar PV, batteries, electrolysers, and electric vehicles, are expected to experience more substantial cost reductions throughout the transition period. These technologies are still in phases of rapid innovation and deployment, and they benefit strongly from learning-by-doing and increasing global demand. Their falling costs make them central to achieving a cost-effective and technologically feasible decarbonization pathway.

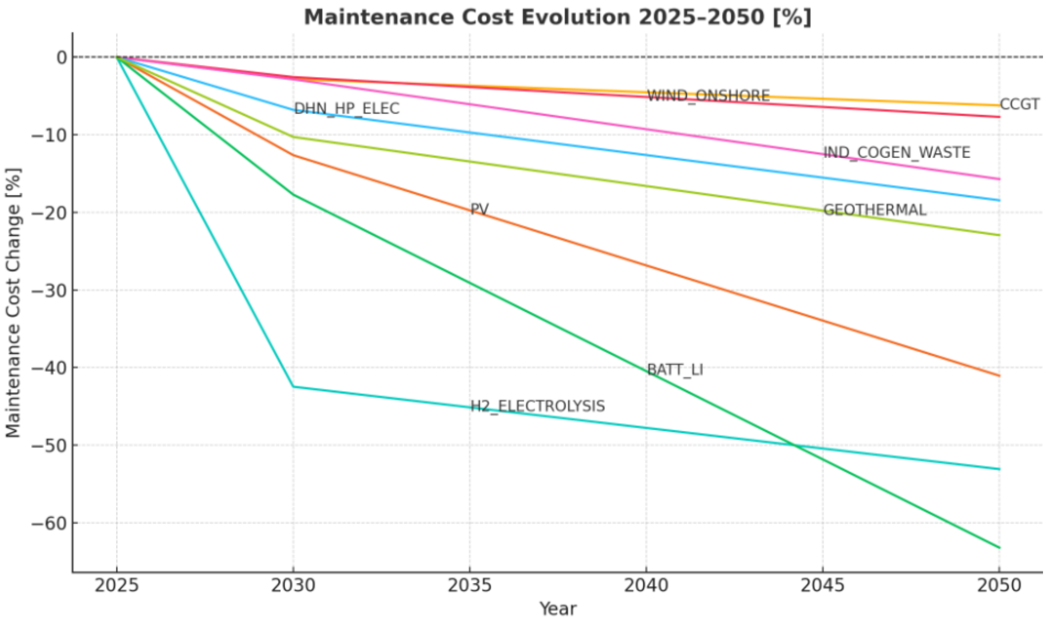

Figure 4.5 – Estimation of maintenance cost tendencies

Notably, the model also accounts for technologies expected to become obsolete. For example, diesel-powered cars and trucks show an increasing trend in investment cost over time. This reflects not only future regulatory restrictions and declining demand but also the rising costs of maintaining compliance with tightening environmental standards in a shrinking market. These upward trends discourage continued reliance on fossil-based transport technologies and push the system toward cleaner alternatives.

Technologies share of supply

In the Italian case study, specific limitations were imposed on the use of certain non-renewable technologies in order to guide the optimization toward more sustainable system configurations. This decision was necessary because some technologies, although economically attractive due to low operational costs and existing infrastructure, would otherwise remain dominant in the absence of explicit restrictions, delaying the transition away from fossil-based systems.

For instance, in the electricity generation sector, the model was forced to follow a linear decrease in the use of CCGT (Combined Cycle Gas Turbines). Without this constraint, the optimization would tend to maintain or even increase reliance on gas-fired electricity, as the infrastructure is already in place and presents very low short-term costs. This would result in a decarbonization pathway inconsistent with long-term climate targets.

In the industrial heating sector, the use of waste combustion and wood was also explicitly limited. Without such a cap, the model tended to allocate over half of all industrial heat production to these two resources, an outcome considered unrealistic and unsustainable given the physical and logistical limits of these feedstocks.

For decentralised heating, fossil-based technologies such as light fuel oil (LFO) and natural gas boilers were also restricted in their use. These measures were introduced to allow space for the model to shift toward cleaner alternatives, such as heat pumps and solar thermal systems, which otherwise remained underrepresented due to their higher initial investment costs.

Lastly, in the transport sector, a limit was placed on the use of CNG buses (compressed natural gas). Although these vehicles are often seen as a transitional solution, Italy's already high gas consumption made it necessary to cap their share at 30% of the bus fleet. Without this restriction, the model frequently opted to expand CNG use well beyond reasonable levels, making it difficult to decarbonize the transport sector in line with national objectives.

Efficiencies

Conversion efficiencies are a key parameter in energy system modelling, as they determine how much input energy is needed to deliver useful energy services. In our framework, efficiency improvements directly affect energy consumption, fuel use, emissions, and the competitiveness of different technologies.

Figure 4.6 illustrates the projected evolution of efficiency for several technologies from 2015 to 2050 in the Limpens study [54]. While all technologies improve over time, the pace of improvement varies. Fuel cell vehicles and electric mobility systems show the steepest gains, making them increasingly relevant in long-term decarbonization pathways. In contrast, conventional technologies such as diesel or gasoline vehicles show only limited improvements. Other systems like heat pumps, electrolysers, or CCGT plants improve moderately.

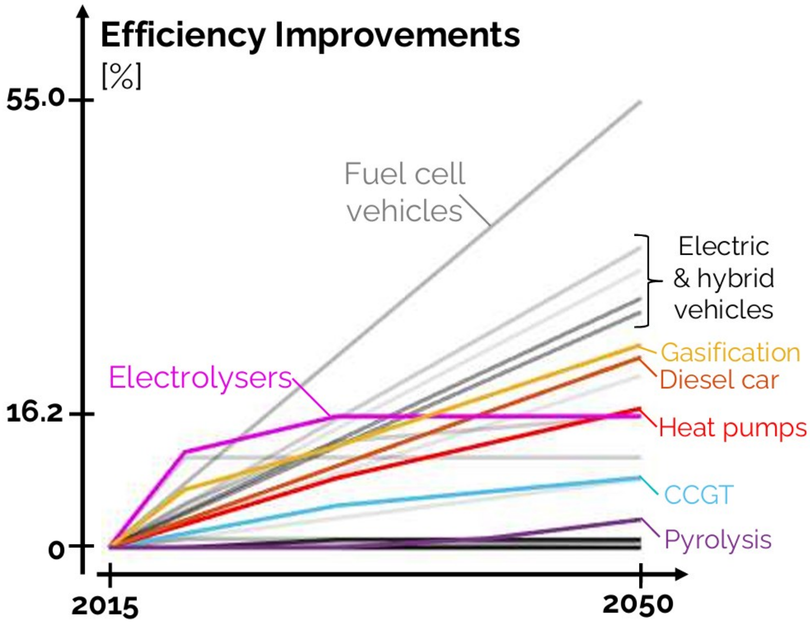

Figure 4.6 – Estimation of efficiency tendencies

The efficiency trajectories adopted in this study are directly based on those developed by Gaultier Limpens for the Belgian version of EnergyScope Pathway. Given the generality of these trends and their basis in international technological developments, the same values have been retained for the Italian case. For widely standardized technologies such as CCGT or PV, efficiencies are assumed to be identical across countries, as their technical performance does not vary by location.

Other

Beyond cost and efficiency, a range of secondary parameters are required to fully define each technology in the model. In this study, most of these values were retained from the original Belgian EnergyScope Pathways dataset developed by Gaultier Limpens [54], with only minimal adjustments for the Italian context.

To begin with, the capacity factors of technologies (c_p)—which define the average output relative to installed capacity—were adapted based on the values provided by Borasio and Moret for Italy [14]. However, their evolution trends over time were aligned with those used by Limpens, ensuring consistency across the time horizon.

Other parameters, such as the technical lifetime of each technology (lifetime), were adopted directly from the Belgian model. These values depend on physical and engineering characteristics that are largely independent of national context, making it reasonable to assume they apply equally to the Italian case.

As for storage technologies, parameters such as $\%sto_{avail}$ (which defines the Storage technology availability to charge/discharge), sto_{loss} (energy lost during storage cycles), and the charge/discharge times ($t_{sto,in}$ and $t_{sto,out}$) were also mostly kept unchanged from the original Belgian dataset.

Nonetheless, some important adaptations were made for technologies where differences between the Belgian and Italian systems are more relevant. For example, in the case of pumped hydro storage (PHS), several parameters used in the Belgian version differ from those assumed by Borasio for Italy [14], especially in terms of capacity installed. To better reflect the reality of the Italian system, we opted to adopt the PHS values from Borasio's dataset. A similar approach was taken for other storage technologies (lithium batteries, EV batteries, plug-in hybrit batteries and daily thermal storage in DHN), where Italian-specific characteristics were considered more representative. In both cases, using Borasio's values [14] provides greater accuracy and coherence with Italy's real storage infrastructure.

These adjustments ensure that while the model maintains structural consistency with previous EnergyScope studies, it remains tailored to the Italian energy system, especially in areas where the national context has a direct impact on technological performance.

4.5 Year 2025: The starting point

In order to simulate the evolution of the Italian energy system from 2025 to 2050, it is essential to provide a consistent and well-defined initial state. This first year acts as a reference point and starting condition from which the optimization can build transition pathways. For this reason, a dedicated input file, PESTD_initialise_2025.mod, is used to define all the required variables and system constraints for the year 2025.

This initialisation file includes several types of information. First, it defines the electricity generation mix by technology, which was derived from data from the International Energy Agency (IEA)[56] and from the internal work of the university's research group. These values set the total amount of electricity produced by each technology (e.g., gas, hydro, solar PV, wind, etc.) in 2025, providing a snapshot of the real system before any optimization occurs.

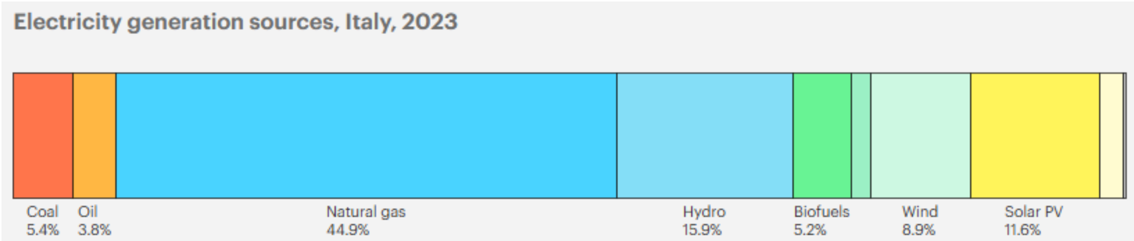

Figure 4.7 – Sources of electricity production in Italy (IEA, 2023)

In addition to electricity production, the model also fixes the production and importation of biofuels for the same year. These values, again based on IEA and internal sources, define the role of bioenergy in the starting mix and ensure that all input flows are accounted for at the beginning of the simulation.

The file then specifies the shares of transport demand met by different technologies or technology layers. This includes the breakdown between public and private transport, as well as the shares of cars, trains, buses, trucks, and other modes. These shares were extracted from the Energy Transition Model (ETM) platform, which offers reliable and updated data on sectoral energy usage.

Finally, the model defines the heat supply structure in 2025. This includes the technology shares used for high temperature heat demand, decentralised low-temperature heating (DEC), and district heating networks (DHN). Each of these categories is assigned an initial distribution of technologies (e.g., gas boilers, heat pumps, cogeneration units). To define these heat technology shares, the approach taken by Borasio in his 2015 study was used as a general reference (shown in Figure 4.8). Although there is a ten-year gap between that study and the starting year of this model, some structural aspects of the Italian heat supply remain comparable. Key elements of Borasio's work were updated using more recent data from the IEA and other available sources, allowing the model to maintain internal coherence while reflecting the technological evolution that has taken place since 2015.

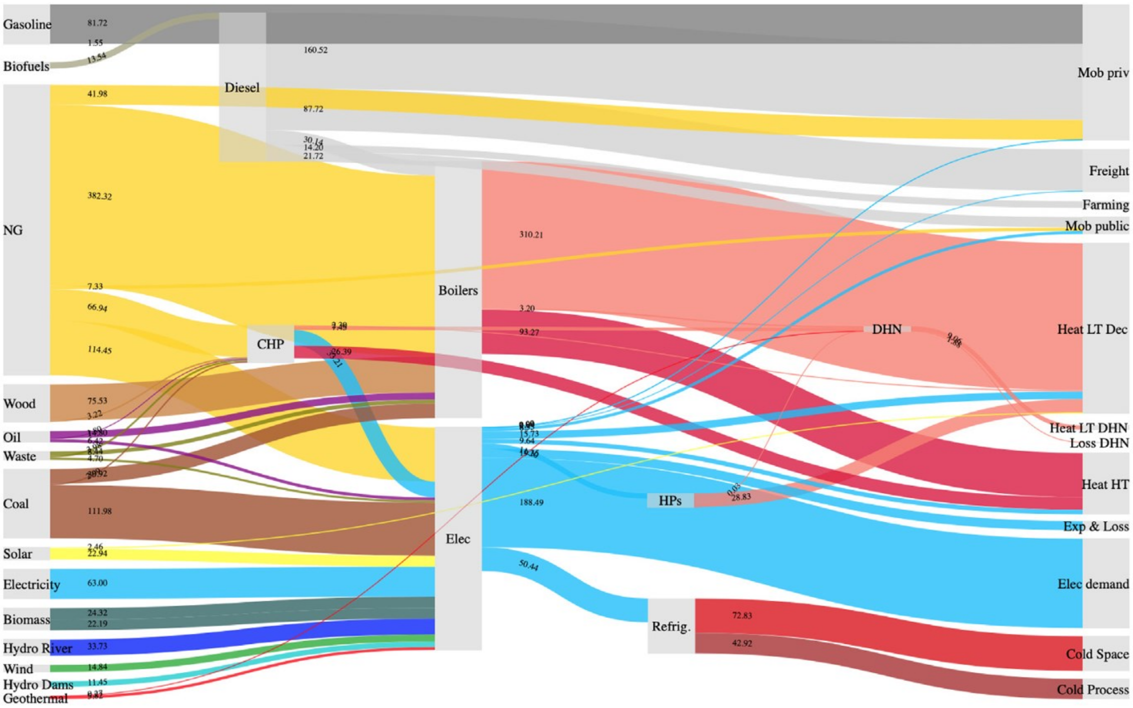

Figure 4.8 – Sankey of Italy's energy system in 2015 (Borasio and Moret [14])

5. Results

In this section, the results of the EnergyScope Pathway for Italy are presented. A simulation was carried out using the energy system defined in the previous chapter. The simulation imposes a cumulative greenhouse gas emission maximum budget (GWP_{budget}) of 4,500,000 $ktCO_2$-eq, a value derived by linearizing the emissions from a baseline of arround 330,000 $ktCO_2$-eq associated with the Italian energy sector in 2025, down to a reduction target of 20,000 $ktCO_2$-eq. This trajectory is designed to ensure a progressive and ambitious reduction in emissions, while also guaranteeing that for the year 2030, annual emissions do not exceed 190,000 $ktCO_2$-eq, thus securing compliance with the European decarbonizations targets that aim to reduce the emissions a 55% from 1990 values.

The following subsections present the main findings. First, we examine the evolution of primary energy sources over the course of the transition, identifying the key trends and structural shifts in the energy mix. This is followed by an analysis of the deployment and changing roles of different technologies across the main end-use sectors. Finally, we assess the economic impact of the energy transition, evaluating system costs and the investment requirements associated with deep decarbonizations.

5.1 Primary energy mix

Figure 5.1 presents the evolution of the primary energy mix in the analysed system between 2025 and 2050. During this period, total primary energy supply (TPES) decreases sharply by approximately 52,7%.

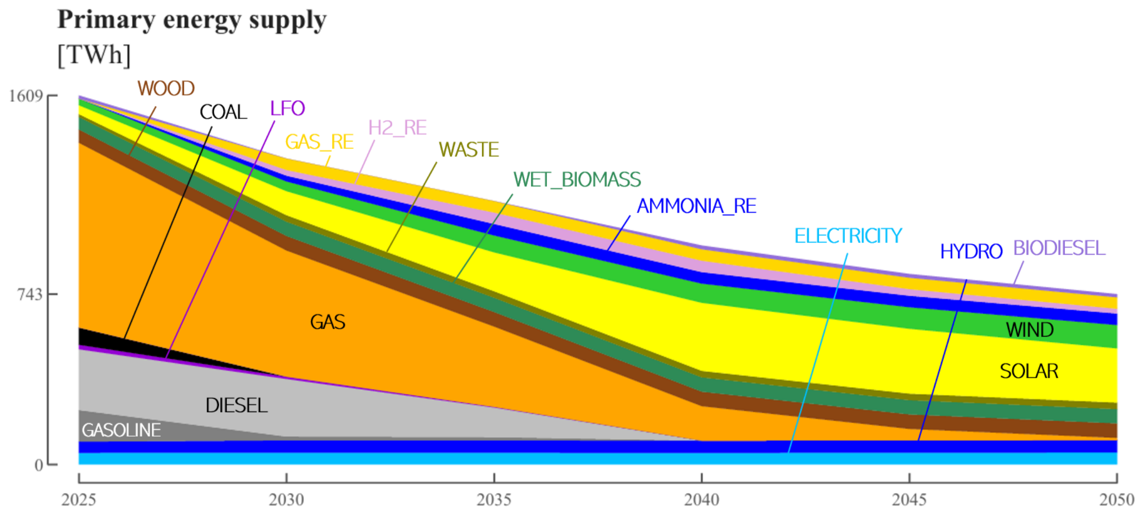

Figure 5.1 – Primary energy mix [TWh]

This marked decrease in primary energy demand is mainly due to the progressive replacement of non-renewable resources, such as natural gas, coal, diesel, gasoline, and light fuel oil, with renewable energy sources and also due to decreasing end use demand (EUD) of certain sectors. In conventional fossil-based systems, electricity is often obtained through thermal processes (e.g., combustion in power plants or engines), which are typically characterized by relatively low conversion efficiencies. In contrast, the increased deployment of renewable electricity technologies, such as hydropower and PV, enables a much more direct and efficient conversion of primary energy into useful energy services.

A key pillar of this transition is the large-scale integration of intermittent renewable energy sources, particularly wind and solar. However, the role of synthetic fuels, whether imported or produced domestically from wood or wet biomass, is also crucial. These energy carriers are not subject to intermittency, thus providing security of supply and flexibility to the system. Moreover, synthetic fuels allow for the continued use of existing infrastructures such as pipelines, storage facilities, and end-use equipment, that was originally designed for natural gas, by substituting it with artificially produced gas, renewable or not. This feature enables the energy system to avoid or delay costly investments in new infrastructure, thereby facilitating a smoother and more economically viable transition.

As a result, less primary energy is required to satisfy the same or even a growing final energy demand. By 2050, the energy mix is dominated by renewables, with significant contributions from wind, solar, biomass, and waste, as well as a growing share of synthetic renewable fuels (e.g., renewable hydrogen, biodiesel, and renewable ammonia). This transition is further supported by a substantial electrification of end-use sectors, allowing for higher overall system efficiency and enabling deep decarbonization.

In summary, while fossil energy carriers are still predominant at the beginning of the transition, by 2050 the system is almost entirely supplied by renewable and low-carbon energy vectors. This profound change not only ensures a drastic reduction in greenhouse gas emissions but also increases energy efficiency and system sustainability, laying the foundation for a resilient low-carbon future.

5.2 Electricity

The decarbonization of Italy's electricity sector is characterized by a series of profound technological and structural changes throughout the transition period. One of the most decisive milestones is the complete phase-out of coal in 2030, a policy choice that firmly frees Italy from one of the highest-emitting energy sources. While coal is eliminated early, natural gas remains present throughout the transition. Initially, combined cycle gas turbines (CCGT) constitute the dominant gas-fired technology, but their use is gradually reduced over time, as is the role of cogeneration. However, cogeneration units retain a significant function, as their ability to simultaneously provide electricity and high-temperature heat is critical for meeting industrial demand, particularly in processes where direct electrification is not feasible. Notably, towards the end of the transition, almost all of the gas used in power generation is either consumed as renewable gas or synthetically produced within Italy, thereby sharply reducing the sector's carbon footprint.

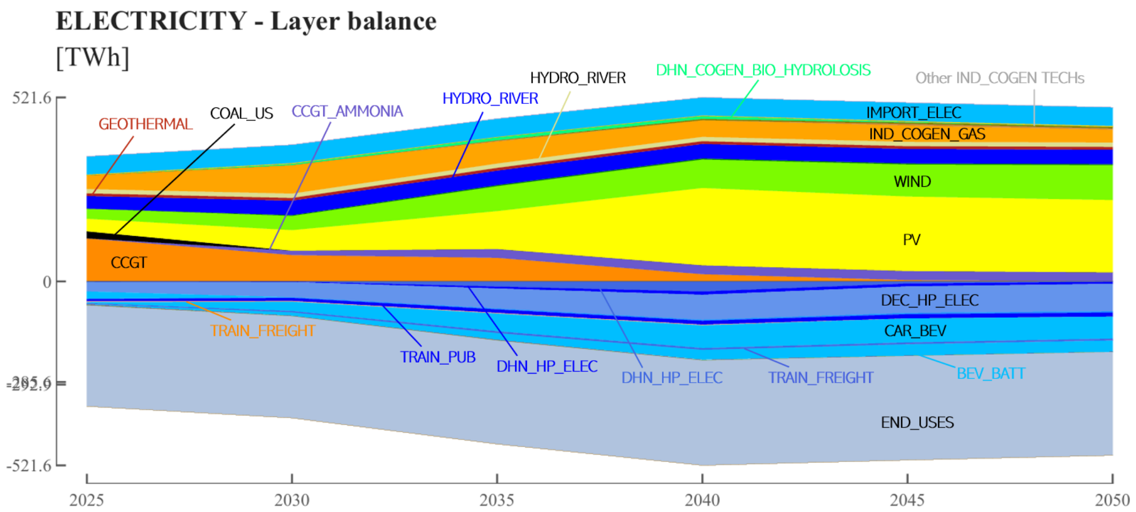

Figure 5.2– Electricity layer balance, detail of production and consumption [TWh]

Solar and wind energy undergoes particularly robust growth during the transition. As fossil-based generation technologies recede, both photovoltaic and wind capacity expand dramatically to meet rising electricity demand, not only for traditional end-uses, but also for new thermal applications enabled by electrification. This trend reflects Italy's strong natural resource potential, especially given its southern European location, which, like other countries like Spain or Portugal, supports large-scale photovoltaic deployment. The evolution of these trends is illustrated in Figure 5.2, which shows how solar, and wind become the backbone of electricity production as the transition advances.

Other renewable sources, such as hydro river, hydro dams, and geothermal, provide a steady and reliable contribution across the entire period. Although their scope for further growth is more limited compared to solar and wind, these technologies play a key role in providing system stability and dispatchable capacity, thus helping to manage the variability inherent in intermittent renewables.

To further strengthen the robustness of generation capacity and reduce dependence on renewable intermittency, the deployment of combined cycle turbines using ammonia (CCGT_AMMONIA) emerges as a pivotal solution, particularly in the latter years of the transition. This technology offers a relatively low-cost, flexible generation option and utilizes renewable ammonia imported from abroad, ensuring secure electricity supply without incurring significant emissions.

Despite the considerable expansion of domestic renewable generation, Italy's power system continues to rely on electricity imports from neighboring countries. The modelling results show that, whenever available, imported electricity is fully utilized since it does not require new domestic infrastructure and is assumed emission-free. Most of Italy's electricity imports originate from Switzerland and France, two countries with some of the lowest electricity-related emissions in Europe, which further enhances the decarbonization of the national electricity mix.

It is also important to note that Figure 5.2 reflects not only the evolution of electricity production, but also the growing and diversifying demand for electricity across different sectors. While most of the generated electricity is dedicated to the End Use layers (electricity and lightning), a significant share is also directed to heat generation and mobility. Regarding heat, most of the electricity is supplied to heat pumps, both decentralized (DEC) units and those serving district heating networks (DHN), supporting the electrification of the heating sector. A smaller but non-negligible portion is allocated to high-temperature heat production for industrial processes, a sector where electrification is less remarkable but increasingly necessary for full decarbonization.

In the mobility sector, a considerable share of electricity is used to power private vehicles, which constitute the largest portion of mobility-related electricity demand. Nonetheless, both passenger and freight trains also absorb a meaningful, but much smaller, fraction of the total electricity supplied to the transport sector. This multifaceted allocation of electricity highlights the central role of electrification not just in traditional power supply, but also as a cross-cutting enabler for decarbonization in both heating and mobility.

As illustrated in Figure 5.2, the transition in Italy's electricity sector is achieved through an early coal phase-out (characterized in the inputs given the recent policies on the matter), a progressive replacement of gas by renewable and synthetic alternatives, rapid expansion of wind and solar capacity, stable output from hydro and geothermal, targeted deployment of ammonia-fueled CCGT for flexibility, and a sustained reliance on low-emission imports. These changes are closely intertwined with the increasing and diversified end-use demand for electricity, which now serves not only conventional consumers, but also heating and mobility applications on a large scale. This integrated approach ensures that Italy's electricity system remains robust, flexible, and sustainable while meeting increasing demand and supporting the wider decarbonization of the entire energy system.

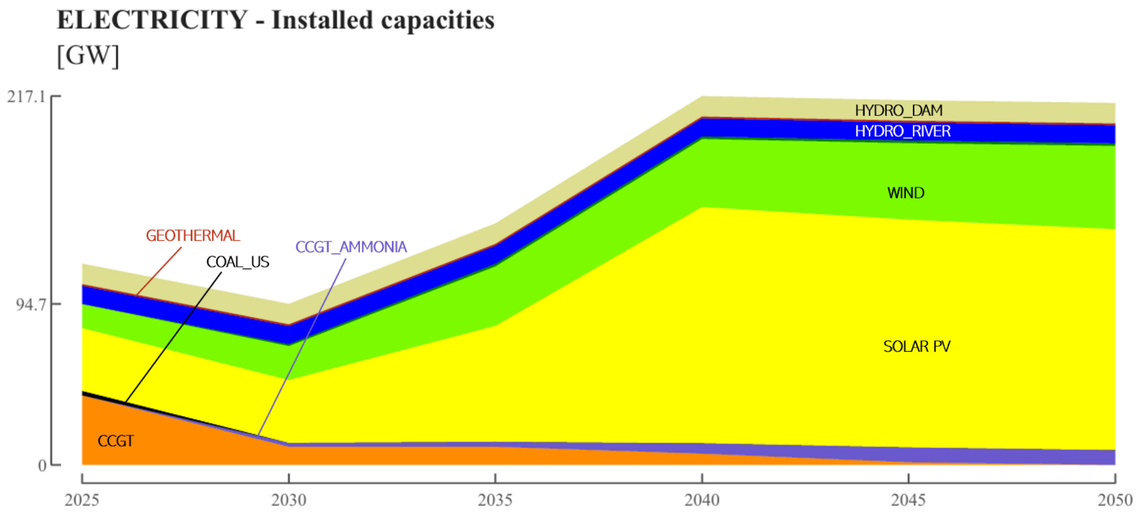

Figure 5.3– System's installed capacities for electricity generation [GW]

The evolution of installed electricity generation capacities over the transition period is illustrated in Figure 5.3. A clear expansion of renewable energy sources is observed, with both wind (onshore and offshore) and photovoltaic (PV) capacities experiencing substantial growth. These two technologies become the main pillars of the future electricity system, reflecting both their economic feasibility and the favorable resource potential in Italy.

In contrast, other renewable sources, such as hydropower (both river and dam) and geothermal energy, do not expand significantly beyond their initial levels. Their development is essentially capped by existing resource limitations, resulting in relatively stable installed capacities throughout the transition. Table 5.1 below provides a summary of the different installed capacities for electricity generation technologies throughout the whole transition, all in GW.

	2025	2030	2035	2040	2045	2050
CCGT	41	10,75	10,75	6,68	1,61	0
CCGT_AMMONIA	0,00	2,32	2,97	6,20	8,81	8,81
COAL_US	2,65	0	0	0	0	0
PV	37	37	68,23	139,06	134,06	130,06
WIND	14,19	21,01	36,50	41,50	46,50	50,50
HYDRO_RIVER	10,65	10,65	10,65	10,65	10,65	10,65
GEOTHERMAL	0,95	1	1	1	1	1
HYDRO_DAM	12,02	12,02	12,02	12,02	12,02	12,02

Table 5.1– Installed capacities for electricity generation technologies [GW]

Regarding fossil-fueled power plants, combined cycle gas turbines (CCGT) show a clear decline in installed capacity over time, in line with decarbonisation objectives and the progressive replacement of fossil fuels. Notably, CCGT capacity is increasingly replaced or complemented by CCGT units adapted to run on ammonia, a low-carbon energy carrier. This technological shift allows for flexible and dispatchable generation, while maintaining compatibility with stringent emission targets.

The capacity mix transitions from a fossil-dominated system to one in which variable renewables provide the vast majority of generation, supported by a portfolio of existing hydro and emerging ammonia-based dispatchable technologies.

5.3 Heat

5.3.1 High-temperature heat

The evolution of high-temperature heat supply in industry, as illustrated in Figure 5.4, reveals a significant transformation in both the sources and the technologies involved. At the beginning of the period, the majority of industrial high-temperature heat is provided by conventional boilers using gas, wood, and waste as primary fuels. These technologies dominate the heat supply due to their well-established infrastructure and flexibility in serving diverse industrial processes.

However, as the transition advances, a clear decline in the use of these traditional boilers is observed. In parallel, their cogeneration counterparts, particularly gas, wood, and waste combined heat and power (CHP) units, gradually take over as the main suppliers of industrial heat. This shift is driven by the dual benefit of cogeneration: these technologies can simultaneously produce high-temperature heat and electricity, leading to significant efficiency gains across the system and better integration with the decarbonizing power sector.

Electricity-based heat production, i.e. heating through an electrical resistance, emerges as an increasingly relevant alternative. While not the principal source, the share of electricity in high-temperature heat supply grows over time, reflecting ongoing efforts to electrify industrial processes where feasible and to further decarbonize this challenging sector.

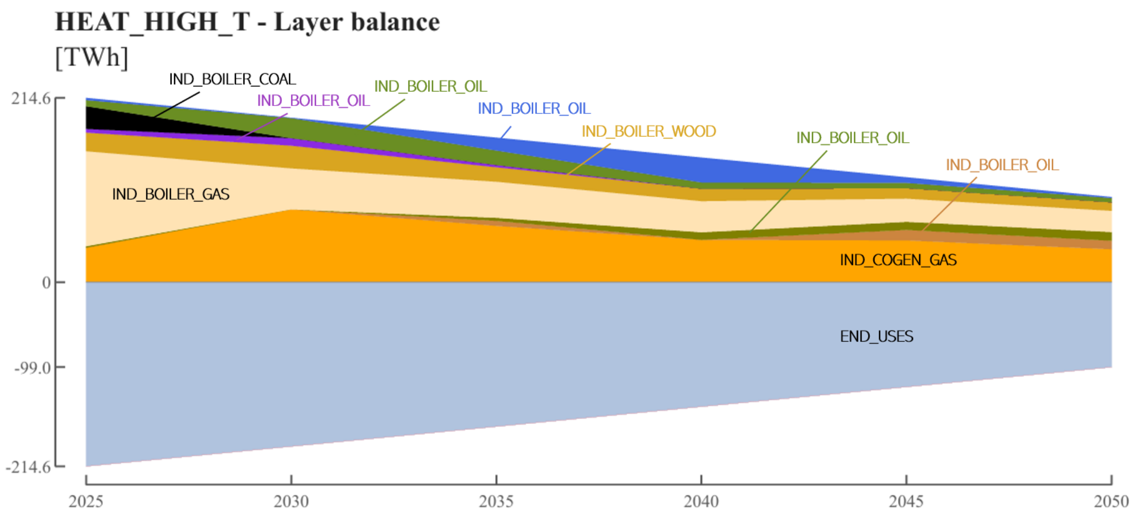

Figure 5.4– Layer balance for high-temperature heat demand [TWh]

5.3.2 Low-temperature heat

In this section, we evaluate the evolution of low-temperature heat demand, which is comprised of two main categories: decentralizing heating (DEC) and district heating networks (DHN). The overall energy demand in this sector shows a declining trend throughout the transition period. This reduction is primarily attributable to several factors, most notably the steady improvement in end-use efficiency and the increasing electrification of the heating sector, which enables the deployment of more efficient heat pumps. Additionally, enhanced building insulation standards contribute to lower heat losses, further decreasing total energy consumption.

It is worth mentioning that, despite the significant development and expansion of DHN infrastructure, the total demand for low-temperature heat continues to decrease. This outcome is explained by the previously mentioned efficiency gains and the fact that some of the demand decrease of decentralized technologies is because that demand is already supplied through DHN, which presents remarkable growth as shown in this chapter.

5.3.2.1 Decentralized heat demand

The decentralized low-temperature heating sector undergoes a radical transformation over the course of the transition, as illustrated in Figure 5.8. At the beginning of the period, this sector is predominantly supplied by fossil fuels, with gas boilers representing the main technology used to meet heating demand. However, as the transition advances, a dramatic shift occurs and traditional fossil fuel-based solutions are progressively phased out, and their contribution diminishes almost entirely by 2050.

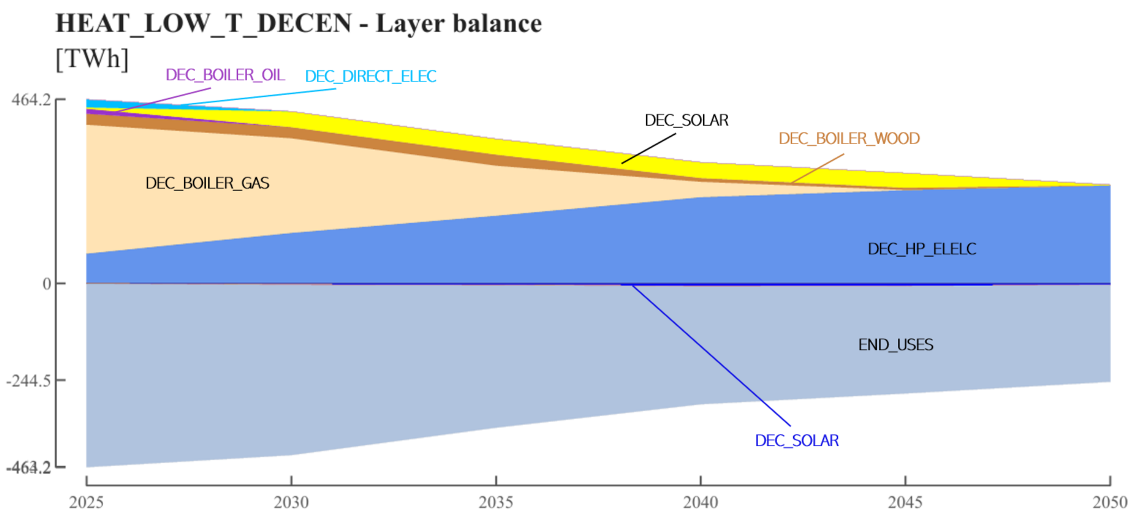

Figure 5.5– Layer balance for decentralized heat demand [TWh]

In their place, heat pumps, an electricity-based alternative, emerge as the dominant technology for decentralized heating. This shift is not immediate: in the early years, solar thermal systems experience significant development and represent an important share of the heat supply. However, as the transition progresses, heat pumps prove to be generally more advantageous than solar thermal in terms of flexibility, efficiency, and year-round applicability. Consequently, as solar thermal units reach the end of their operational lifetimes (just before the end of the transition period), they are not replaced, and their share declines rapidly. By 2050, nearly all decentralized low-temperature heat demand is met by heat pumps.

This is particularly significant, as heat pumps deliver high efficiencies (expressed in terms of coefficient of performance, COP), not by generating heat from fuel combustion, but by transporting ambient heat from the environment into buildings (or the other wat around in the case of cooling). Such a transformation brings substantial benefits: not only does it drastically reduce the direct use of fossil fuels and associated emissions, but it also enables deep decarbonization of a critical sector, provided that the electricity supply itself is clean.

The shift to heat pumps, therefore, represents both a major technological upgrade and a key step toward achieving net-zero emissions in the built environment. The overall result is a sector that transits from being a major emitter to one that is highly efficient and ready for full decarbonization through further progress in the power sector.

5.3.2.2 District heat network demand

The district heating network (DHN) for low-temperature heat presents a notably diversified supply portfolio throughout the transition, as shown in Figure 5.6. This diversification is a direct consequence of a modelling constraint: no single technology is allowed to cover more than 35% of total DHN heat demand. This approach was adopted after previous simulations showed that, without this limitation, technologies such as deep geothermal could end up dominating almost the entire sector—a result that is not currently supported by real-world feasibility at such a large scale.

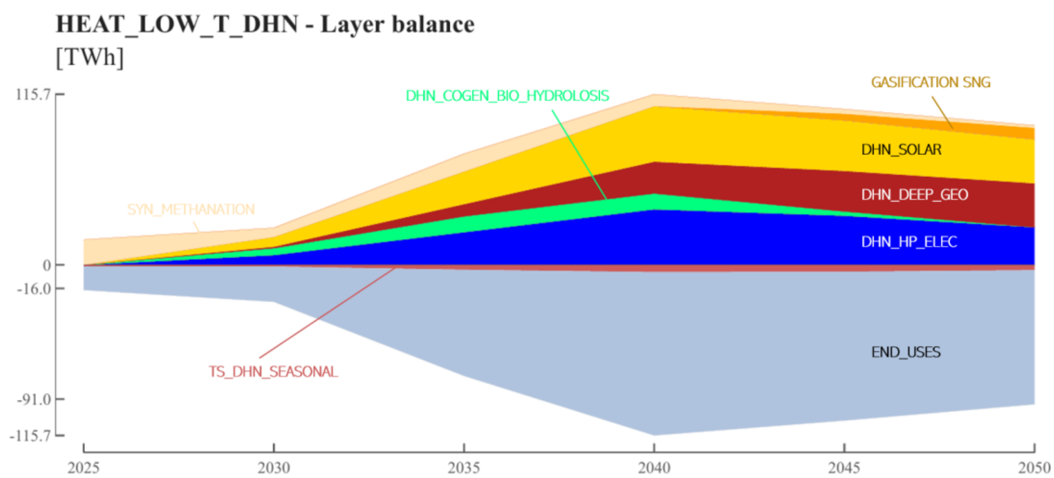

Figure 5.6– Layer balance for DHN demand

As a result, the model yields a balanced mix in which solar thermal, heat pumps, and geothermal sources each contribute a substantial share, collectively satisfying the vast majority of DHN demand. All three are renewable or highly efficient technologies, supporting both decarbonization and reliability. Notably, during the transition, the system also takes advantage of residual heat from industrial processes, such as synthetic methanation (SYN_METHANATION) and synthetic natural gas (GASIFICATION_SNG), which play a non-negligible role as intermediate contributors.

Another important component is the contribution from cogeneration based on bio-hydrolysis, which emerges as a key player during the transition years. By capturing and distributing otherwise wasted heat from this process, the DHN helps with a more efficient use of resources and can create synergies with other sectors by using their residual heat to provide it to the final consumer.

A crucial factor explaining the strong expansion of DHN over the transition is its inherent efficiency: centralizing heat generation and subsequently distributing it to end users allows for the deployment of highly efficient, large-scale technologies that might not be feasible at the individual building level. Despite some distribution losses, DHN proves to be a very effective way to manage heat demand, particularly in densely populated areas where aggregated demand profiles and infrastructure sharing further enhance system-level efficiency.

By the end of the transition period, the DHN's low-temperature heat supply is provided in almost equal parts by solar thermal, heat pumps, and geothermal energy. This diversified and renewable-based approach ensures a robust, reliable, and sustainable heat supply while avoiding excessive dependence on any single technology and taking into account realistic deployment limits. The integration of residual industrial heat and advanced cogeneration further enhances the system's overall efficiency and contributes to the achievement of climate targets.

5.4 Mobility

5.4.1 Private transportation

The private mobility sector experiences a dramatic transformation over the transition period, as depicted in Figure 5.7. Starting from a highly carbon-intensive baseline, dominated by gasoline and diesel vehicles, the sector achieves a near-complete decarbonization by 2045. By this point, almost all private vehicles on the road are fully electric, marking a pivotal shift towards zero-emission mobility.

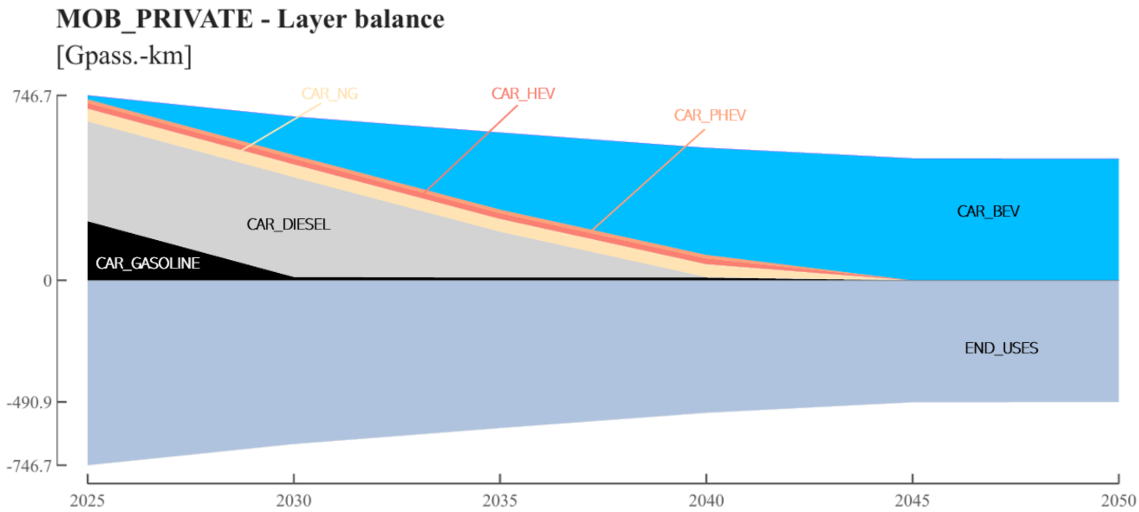

Figure 5.7– Layer balance for private mobility demand [Gpkm]

Natural gas vehicles maintain a visible but relatively minor presence throughout the transition. While they play a notable transitional role, their share remains small compared to the dominance of fossil-fuelled cars in the early years and, later, the overwhelming uptake of battery electric vehicles (BEVs). Hybrid vehicles (HEVs) and plug-in hybrids (PHEVs) also emerge as interesting alternatives during the transition years, providing flexibility and acting as a technological bridge between conventional and fully electric cars. Nevertheless, neither gas-powered nor hybrid vehicles become the predominant technology at any stage.

Ultimately, electric cars (BEVs) become the undisputed solution for private mobility, supported by advances in infrastructure, declining battery costs, and strong social acceptance. As a result, alternative fuels such as gas and biodiesel are increasingly used for more critical applications, such as heavy-duty freight or heat production (high-heat temperature specifically), where full electrification may be less feasible. This sectoral transition not only eliminates direct emissions from private vehicles but also helps decouple mobility from fossil energy sources, provided that the electricity system continues to decarbonize in parallel.

5.4.2 Public transportation

Public transportation shows a clear upward trend over the course of the transition, with total (giga)passenger-kilometres [Gpkm] steadily increasing. Rail-based public transport is by far the predominant mode, consistently accounting for more than three-quarters of total public mobility demand both at the start and at the end of the transition period. This dominance is due to the high efficiency, capacity, and electrification of trains and tramways, which require little technological change, beyond scaling up their use, since they already rely on electricity from the beginning (2025).

The most significant changes occur in road-based public transportation. Initially, diesel buses constitute the main technology. However, by 2050, the landscape is far more diversified: hydrogen fuel cell buses become the leading technology for public road transport, followed by CNG (compressed natural gas) buses and, to a lesser extent, diesel buses. It is important to note that by the end of the period, all diesel buses operate exclusively on renewable diesel, making this segment compatible with a low-carbon future.

A notable feature during the transition is the role of hybrid diesel buses, which act as crucial bridging technology. As traditional diesel is phased out, hybrid buses contribute significantly to satisfying public transport demand in a more sustainable manner. While they are ultimately surpassed by fuel cell and gas buses in the final technology mix, hybrids provide a vital intermediate step, enabling a smoother and more flexible transition towards fully renewable options.

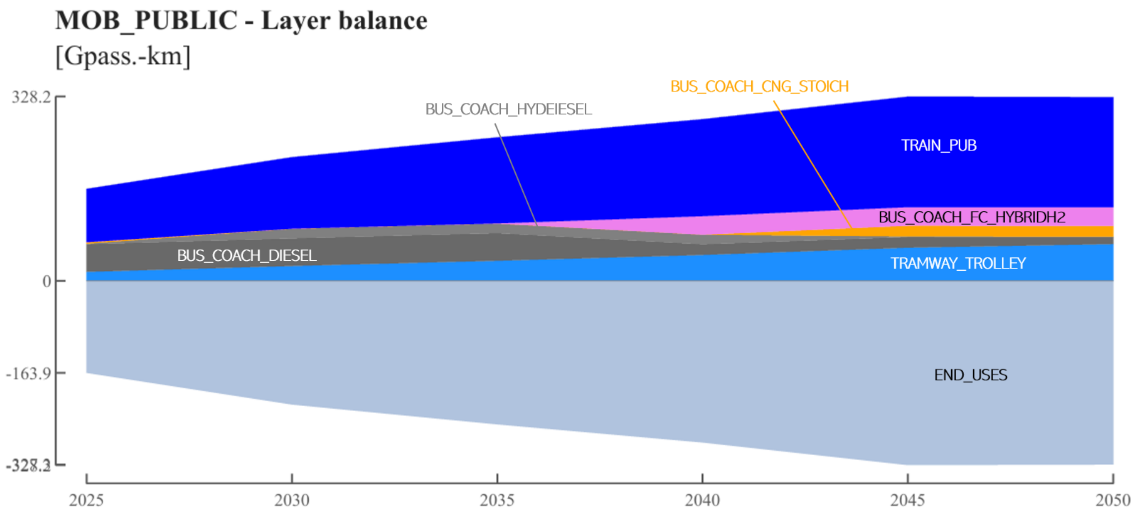

Figure 5.8– Layer balance for public mobility Gpkm]

Overall, the sector evolves towards a highly electrified and diversified public transportation system, with rail remaining the backbone of passenger movement and road-based technologies shifting decisively towards low- and zero-emission solutions.

5.4.3 Freight transportation

The evolution of freight transport modalities and fuels is illustrated in Figure 5.9. In this section, it is important to note that the overall energy use demand (EUD) for freight transport is projected to decline significantly over the transition. Despite this decline in total demand, the share of freight satisfied by rail increases considerably, so much so that, in absolute terms, the amount of freight transported by rail is essentially doubled over the period.

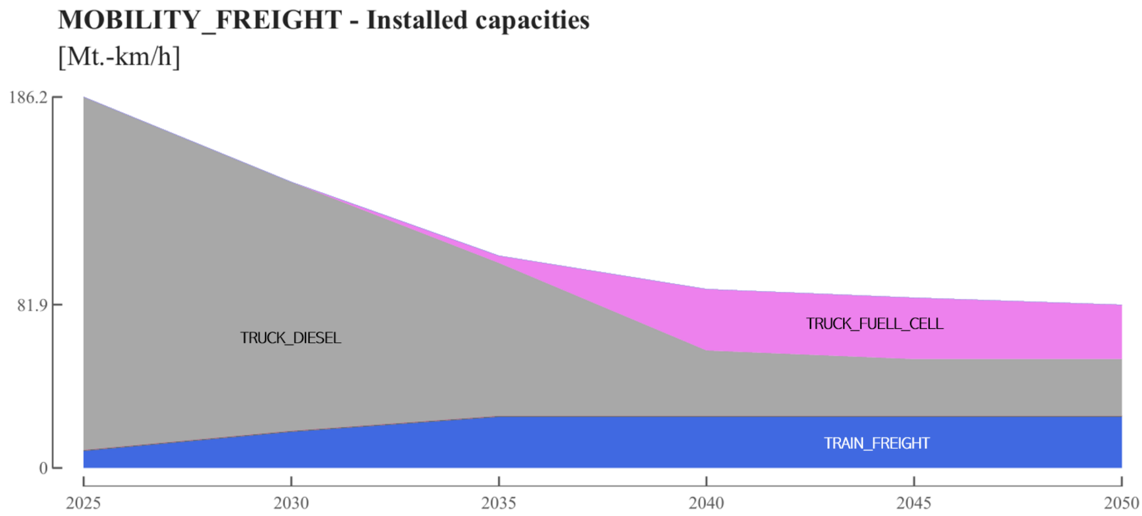

Figure 5.9 – Installed technologies for freight transportation [Mtkm/h]

Up to 2035, the increase in rail freight not only accommodates overall growth in its own mode but also substitutes for a portion of road freight transport, reflecting a clear modal shift enabled by the high efficiency and existing electrification of Italy's rail network. This is visible in the graph, where the blue segment expands, while road transport (grey area) contracts.

After 2035, the main changes are seen within road freight itself: there is a marked transition from traditional diesel trucks to hydrogen fuel cell trucks, which increasingly replace diesel as the dominant technology for long-haul and heavy-duty applications. Notably, both fuel cell trucks and diesel trucks are powered by sustainable fuels: the hydrogen is green hydrogen (imported), and the diesel is increasingly biodiesel. This transition ensures that, even as a share of diesel trucks persist, the emissions intensity of the sector remains low and aligned with decarbonizations objectives.

Overall, the freight sector moves from a conventional fossil-based configuration to a more diversified and sustainable portfolio. Rail, with its robust efficiency and full electrification, more than doubles its absolute activity and takes an ever-greater share of the shrinking total demand, while road freight adopts a combination of fuel cell and biodiesel trucks. This dual strategy not only supports the achievement of emission reduction targets, but also enhances system resilience and takes advantage of Italy's established rail infrastructure and emerging low-carbon technologies for road transport.

5.5 Costs

Figures 5.10, 5.11, and 5.12 illustrate the evolution of the system's annual costs, cumulative investment (CAPEX), and operational expenditures (OPEX, both operational and maintenance, including costs of supply) throughout the transition pathway. One of the most remarkable features of the results is the relative stability of the total annual system cost, which remains almost constant, rising only slightly from 261,98 b€$_{2015}$ in 2025 to 256,56 b€$_{2015}$ in 2050, being 2040 the year in which costs peak at 263,88 b€$_{2015}$. This stability is achieved despite a profound transformation in the structure of costs and underlying technologies, reflecting both the phasing out of fossil fuels and the scaling up of new infrastructure and renewable energy technologies.

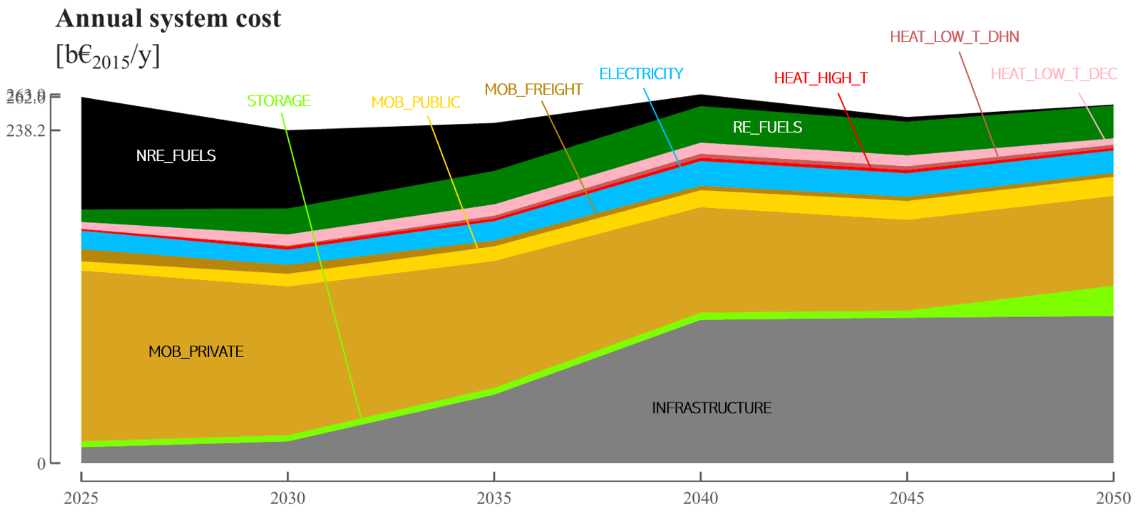

*Figure 5.10 – Total annual system cost per year [b€$_{2015}$/*year*]*

A central methodological aspect of the analysis is the consideration of the residual value for investments whose lifetimes exceed the time horizon of the study (i.e., beyond 2050). As previously described (Section 3.2.4, Eq. 57), a proportional return on investment is accounted for, ensuring that long-lived technologies are not unduly penalized in the economic assessment. This approach enables rational investment decisions, particularly for assets such as infrastructure or generation plants with long operational lifetimes.

Within the breakdown of system costs, infrastructure investments (1.606 b€$_{2015}$) display a marked increase after 2030, mainly due to the deployment of new grid, which accounts for nearly the 97% of the infrastructure costs. In figure 5.11 we can appreciate that infrastructure costs arise especially during the second and third phase (2030-2040), when the development of wind and photovoltaic technologies is the greatest. Therefore, we can attribute this rise in infrastructure investment costs to the need of integrating these new technologies into the energy system. The remaining infrastructure costs are linked to the development of DHN grid (2% of infrastructure costs) and the remaining 1% to other processes' infrastructure (SMR, GASIFICATION_SNG and BIO_HYDROLOSYS, among others).

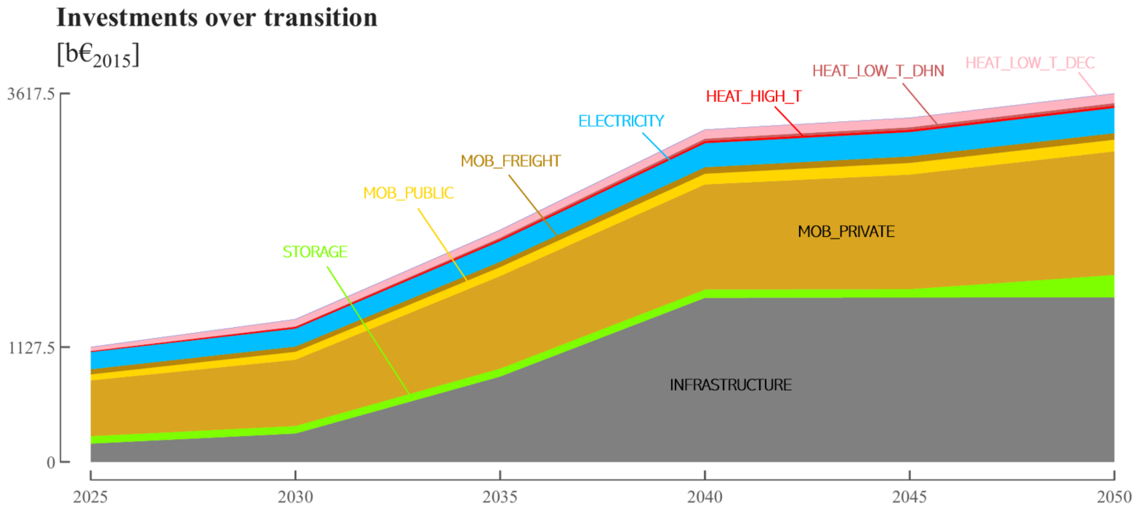

Figure 5.11 –System's investment costs [b€$_{2015}$]

The mobility sector, especially private mobility (1.213 b€$_{2015}$), stands out as a major contributor to cumulative investment costs. This is primarily due to the high energy demand of the sector and the relatively short lifespan of vehicles compared to other technologies. The need for frequent renewal of the vehicle fleet results in consistently high levels of investment throughout the transition. Fully electric, diesel and gasoline vehicles correspond, respectively, to the 43%, 33% and 14% of the layer's investment costs and highlights the high dependency on fossil fuels at the beginning of the transition period. Public mobility and freight also require substantial investments, each contributing with 114,92 b€$_{2015}$ and 64,19 b€$_{2015}$.

The electricity sector is another significant driver of capital expenditures, specifically 215,21 b€$_{2015}$, as it accounts for investments in new generation capacity, such as wind turbines and photovoltaic PV, as well as hydro dam and river, geothermal, CCGT and any other technology that generates electricity. These investments are critical to the successful decarbonization of the energy system and enable the progressive electrification of end-use sectors. As expected, PV development costs stand out in this layer, with a cumulative cost of 86,86 b€$_{2015}$. Costs associated with GGCT plants and wind technology also contribute notably to the investment expenditure of this sector, respectively accounting for 27,19 b€$_{2015}$ and 34,21 b€$_{2015}$.

A particularly noteworthy aspect is the trend of storage costs (256,07 b€$_{2015}$), which remain remarkably constant over the entire transition period. The storage component is dominated, capacity-wise, by thermal storage associated with district heating networks and gas storage. However, towards the end of the transition, the system begins to incorporate pumped hydro storage (PHS), which accounts for 73% of the whole storage-related investment. This late-stage investment occurs as the electricity sector's reliance on renewable sources increases and the role of dispatchable fossil-fuel generation declines. Until the final phases of the transition, electricity supply remains a bit dependent on combustion technologies and renewables intermittency, arising the immediate need for large-scale electricity storage. Investment in pumped hydro storage is the safest and most economical alternative to maintain reliability and flexibility of the supply.

Finally, there are the heat sectors that do not have a huge impact in the culminative chart but cannot be ignored. Decentralized heating represents the biggest investments out of the three wit 93,97 b€$_{2015}$, while high-temperature heat and DHN represent each 21,7 b€$_{2015}$ and 25,89 b€$_{2015}$.

Throughout the transition, expenditures associated with non-renewable fuels decrease steadily, while costs related to synthetic fuels rise as these technologies are deployed to replace fossil energy carriers. This shift in the composition of fuel costs reflects both the technological evolution and the economic rebalancing of the energy system, in other words, expenditure in fuels shifts from non-renewable to renewable along the transition in a relatively symmetrical way (as the first type decreases the other is gaining it).

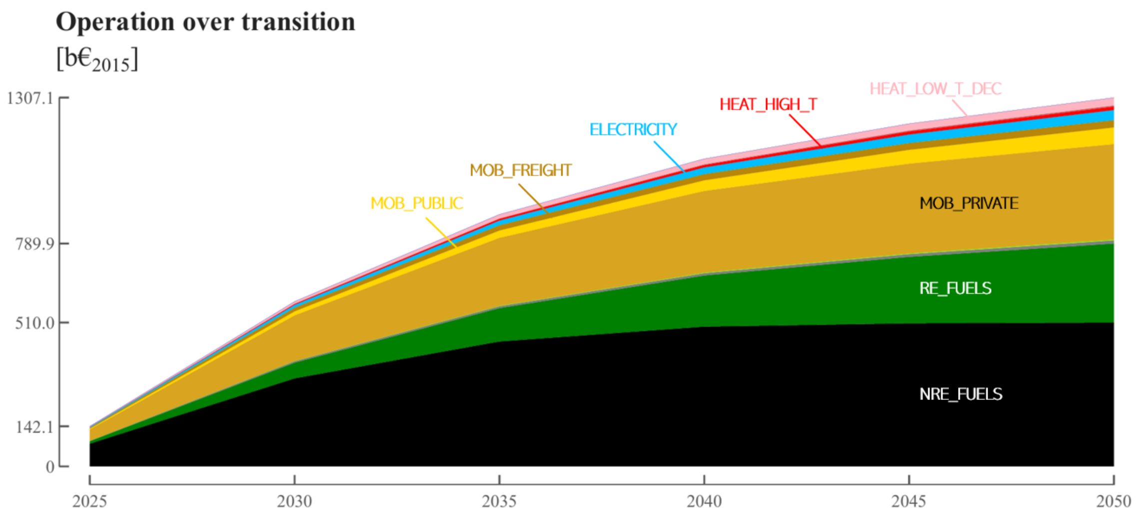

Figure 5.12– System's operational costs [b€$_{2015}$]

Looking at Figure 5.12, it is easy to identify the three main cost drivers for OPEX, these being, in order: non-renewable fuels, private mobility and renewable fuels. Nonrenewable fuels OPEX cost represents the acquisition value of said resources, whish, across all year sum up to 510 b€$_{2015}$ and close to 40% of the total. The operational costs of private mobility basically refer to the maintenance costs that vehicles need to undergo every certain time, at the end of the transition, cars maintenance costs translate to 338,6 b€$_{2015}$. Finally we have the renewable fuels that account for a total of 279,9 b€$_{2015}$.

6. Conclusions

This work represents the first application of the EnergyScope Pathway approach to the case of Italy, introducing a modelling framework never previously used for the analysis of the national energy transition. By employing this pathway model, it has been possible to assess not only the optimal end-state for 2050, but also the cost-effective transition trajectory and intermediate decisions required to achieve deep decarbonization in line with climate targets. The results demonstrate that Italy's energy transition is indeed feasible within the defined technical and economic boundaries, provided that certain key conditions are met.

A central outcome of the study is the confirmation of three key pillars that must support the transition: reduced final energy demand, large-scale deployment of renewable energy sources, and broad electrification of end uses. Importantly, the first pillar—reduction in energy demand—is not an endogenous result of the model but is based on external projections from European and national studies. It assumes reduced end use demand due to macroeconomic and demographic trends, as well as ambitious energy efficiency improvements across all sectors, driven by technological progress, thermal insulation, behavioral shifts, etc. The second and third pillars—the expansion of renewables and the electrification of end uses—are core outputs of the optimization and emerge as critical levers for system decarbonization. These three elements are interdependent and should evolve in parallel to ensure a successful energy transition. These three factors are inseparable and must progress in parallel to enable the full decarbonization of the system.

It is, however, essential to recognize several constraints and nuances that emerge from the results. While renewables will form the basis of Italy's energy supply, the use of fuels, whether imported or domestically produced, remains indispensable. Fuels are required to cover specific demand segments that cannot be reliably satisfied due to the intermittency of most renewable sources, and to serve sectors for which complete electrification is technically or economically prohibitive. For example, certain industrial processes demanding high-temperature heat, and segments of the heavy transport sector, will continue to rely on fuels (ideally renewable or synthetic) even by 2050, leveraging existing infrastructure.

Another critical point is that full electrification of all sectors is not always the optimal solution. Pushing electrification to its theoretical maximum would impose very high loads on the electricity grid, especially during peak demand periods, and the associated network reinforcement costs could become economically prohibitive, as shown in the previous chapter, grid deployment drives up the investment costs remarkably. While fully electrification might be the optimal solution for the far future, such as 2100, the horizon of this simulation was 2050 and full electrification has not been proven as economically feasible. This is why some heat sectors do not present the initially desired electrification rates and, in the meantime, other technologies like DHN prosper a lot in the studied period.

The strategic use and, ideally, domestic production of synthetic fuels is also highlighted as a key enabler. While importing synthetic fuels may provide flexibility, excessive reliance on external supply introduces exposure to potential geopolitical tensions. This was exemplified in the crisis of natural gas supply due to war between Russia and Ukraine, which tensioned a lot of gas-dependent economies. Considering Italy's substantial renewable potential due to its geographical and climatic conditions, maximizing domestic production of these fuels would not only reinforce decarbonization but also enhance national energy independence. This aspect, however, is not directly optimized by the model, which, by construction, minimizes system costs without accounting for additional investment that would be necessary to achieve full energy sovereignty.

It must also be emphasized that the EnergyScope Pathway traced in this study is inherently dependent on the input assumptions: technology costs, resource potentials, demand projections, policy constraints, and many other parameters. As with all modelling exercises of this nature, results should be interpreted within the context of these underlying assumptions; different inputs would naturally lead to alternative transition trajectories and outcomes.

In conclusion, this work demonstrates the value of EnergyScope Pathway as an open, transparent, and flexible modelling tool for national energy system analysis. Its capacity to optimize long-term pathways and support scenario exploration makes it a powerful resource for policymakers and stakeholders aiming to design cost-effective and robust decarbonization strategies for Italy and beyond.

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