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The European power sector toward 'Net Zero by 2050': OSeMOSYS optimization vs IEA Scenarios

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Abstract

This thesis investigates the evolution of the Continental European power sector toward Net Zero Emissions by 2050, addressing two primary research questions: first, whether a simplified, aggregated linear optimization model can produce outputs consistent with IEA WEO 2024 benchmarks; and second, what key trends characterize the European power sector's transformation up to 2050 across various scenarios.

The methodology begins with a critical retrospective analysis, comparing the IEA's World Energy Outlook 2010 and 2024 editions against historical time series (1990–2024). Focusing on CO_2 emissions, electricity generation, and primary energy demand, this phase reveals a systematic underestimation of renewable penetration in past projections in favour of a higher reliance on fossil fuels. Such insights are fundamental for developing the analytical sensitivity required to understand how model structures and initial assumptions critically dictate final outputs.

Following an evaluation of available open-source tools, OSeMOSYS is selected as the ideal framework for the modelling phase. The results demonstrate that a simple, aggregated, cost-minimizing linear optimization approach effectively captures strategic macro-trends and validates the utility of simplified models for strategic insight and long-term energy planning. However, the economic lever alone, specifically declining technology costs and carbon taxes, is insufficient for achieving the full decarbonization of the power sector. The transition toward Net Zero 2050 requires robust policy frameworks to support green technologies and an accelerated phase-out of fossil fuels. Furthermore, the findings highlight that as renewables dominate the energy mix, the role of conventional technologies transitions from primary energy production to the provision of peaking and firm capacity.

Key-words: OSeMOSYS, European Power Sector, Energy Transition, IEA WEO, Energy Model Classification.

Abstract in italiano

Questa tesi analizza l'evoluzione del settore elettrico dell'Europa continentale verso l'obiettivo Net Zero Emission 2050. La ricerca affronta due quesiti principali: se un modello di ottimizzazione lineare semplificato e aggregato possa produrre risultati coerenti con i benchmark del World Energy Outlook 2024 e l'identificazione delle tendenze evolutive del sistema elettrico europeo al 2050 in diversi scenari.

La metodologia parte da un'analisi retrospettiva che confronta le traiettorie dei risultati delle edizioni 2010 e 2024 del WEO con i dati storici (1990-2024). L'analisi rivela una sistematica sottostima della penetrazione delle rinnovabili nelle proiezioni passate a favore dei fossili, evidenziando come le ipotesi ed assunzioni iniziali e le caratteristiche del modello determinino fortemente i risultati delle simulazioni. Sulla base di tali premesse e di una valutazione di vari strumenti open-source di modellazione, OSeMOSYS viene scelto come framework di modellazione.

I risultati dimostrano che un modello semplificato basato sulla sola minimizzazione dei costi cattura efficacemente i macro-trend strategici, confermandosi utile per la pianificazione energetica a lungo termine. Tuttavia, emerge che la sola leva economica, quale il calo dei costi tecnologici e carbon tax in aumento, è insufficiente per la completa decarbonizzazione del settore elettrico Europeo. Il raggiungimento del Net Zero Emission 2050 richiede politiche mirate a sostenere le tecnologie green e favorire un accelerato phase-out dei combustibili fossili. Infine, lo studio evidenzia una trasformazione strutturale per le tecnologie convenzionali: con l'aumento delle rinnovabili nel mix energetico, il loro ruolo evolve dalla produzione di energia primaria alla fornitura di capacità di picco e di riserva.

Parole chiave: OSeMOSYS, Settore Elettrico Europeo, Transizione Energetica, IEA WEO, Classificazione Modelli Energetici.

Contents

Introduction

Context and Motivation

Europe's pathway to climate neutrality by 2050 requires a profound reconfiguration of the power sector, shifting from fossil-based generation toward systems dominated by variable renewable energy (VRE) and a growing portfolio of flexibility resources. Long-term planning is therefore increasingly model-driven. At the same time, many influential institutional scenario exercises rely on highly complex, partly proprietary frameworks that can behave as "black boxes", making it difficult to trace how assumptions, constraints, and modelling choices shape the resulting trajectories and to what extent results are driven by modelling architecture rather than by underlying system dynamics.

To develop the analytical sensitivity required for a robust modelling exercise, this thesis begins with an evolutionary and retrospective assessment of global energy projections. Specifically, it compares the IEA World Energy Outlook (WEO) 2010 projections with historical time series (1990–2024) and with updated pathways in WEO 2024, focusing on total primary energy demand, electricity generation by source, and CO_2 emissions. Because WEO editions adopt different CO_2 emissions accounting methodologies, historical CO_2 series are harmonized to ensure methodological comparability with WEO 2024 using a consistency procedure inspired by the IPCC Time Series Consistency approach. The comparative analysis is designed to evaluate the accuracy and the consistency of past trajectories against historical evidence and to analyze how these projections have been subsequently redefined over time. Comparative evidence highlights a systematic pattern: earlier projections notably underestimated the penetration of renewables (especially PV) and implied a more persistent role for fossil fuels than subsequently occurred. This retrospective evidence provides the incipit of the thesis. It shows that projection accuracy is not guaranteed by model complexity alone, as results remain strongly dependent on model structure, assumptions, and input choices. This motivates the adoption of a simplified and aggregated modelling approach and directly frames RQ1, which tests whether an aggregated least-cost optimization model can reproduce WEO 2024 system-level trends under a consistent set of inputs.

Research Questions and Scope

Within this context, the thesis addresses two research questions:

1. **RQ1:** Can a simplified, aggregated linear optimization model, focused solely on cost minimization, produce trends and outputs consistent with those of

the IEA WEO 2024 Europe scenarios given a consistent set of input parameters?

2. **RQ2:** Building on the modeling framework established for the benchmarking in RQ1, identify the long-term systemic implications and structural shifts arising from the Continental European power sector's evolution across the three modeled scenarios.

While RQ1 assesses the methodological validity of simplified modelling through a structured benchmarking exercise against WEO 2024, RQ2 stems from the geographical scope of the analysis. Given that the modelling boundary is Continental Europe, the thesis also aims to characterize the system-wide transition trends of the European power sector to 2050 across the modelled pathways. Beyond consistency with an external benchmark, the scenario runs are therefore used to identify how the generation mix, firm capacity requirements, and flexibility needs evolve under different levels of climate ambition within a purely economic, least-cost optimization framework.

Model Simplification Strategy

A central design choice of the thesis is to deliberately reduce modelling complexity. The model is a single-region representation of Continental Europe with a single region assumption, with a limited and aggregated technology set, and a deterministic linear formulation whose objective function focuses exclusively on minimizing total discounted system costs. Complexity is thus reduced along three main dimensions: geography (one region), technology detail (few representative technologies), and behavioural structure (least-cost optimization only), to examine whether a simplified framework can still capture robust system-wide patterns.

Methodological Overview

To answer the research questions, the thesis follows a staged methodological flow that moves from critical awareness to model implementation and interpretation. The approach is explicitly structured as follows:

- review of energy-model classification schemes and identification of relevant modelling paradigms,
- translation of the literature review into explicit functional requirements for the analytical framework,
- selection of the modelling tool through a comparative assessment of four candidate tools (oemof, Balmorel, Calliope, and OSeMOSYS),
- formal characterization of the selected framework OSeMOSYS, including its operational logic, core equations, and input–output structure,

- definition of the optimization problem and specification of scenario assumptions consistent with WEO 2024 and IEA narratives,
- construction of an aggregated dataset for Continental Europe and calibration of the 2024 base year,
- execution of scenario simulations and post-processing of model outputs,
- synthesis of findings, including critical discussion of methodological limitations and avenues for improvement.

Based on the retrospective findings (Chapter 1), the thesis reviews the principal classification schemes for energy models in the literature (Chapter 2) and translates them into explicit modelling requirements (Chapter 3). These requirements include a bottom-up capacity-expansion and dispatch framework, intertemporal linear optimization, a total system cost–minimization objective function, and tractable complexity. A focused screening and comparison of candidate tools leads to the selection of OSeMOSYS, implemented through the MUIO (Modelling User Interface for OSeMOSYS) support model implementation, data handling, and scenario execution in a consistent environment. Chapters 3 and 4 then detail the core logic of OSeMOSYS, its key inputs and outputs, and the main equations underpinning its capacity-expansion and dispatch decisions. In this thesis, OSeMOSYS is used as a deterministic, perfect-foresight, least-cost optimizer: it identifies investment and operation trajectories that meet electricity demand across years and time steps while minimizing total discounted system costs, subject to scenario-specific assumptions and constraints.

The technology portfolio is aggregated and intentionally limited to options that are either (i) currently widely deployed in the European power sector or (ii) the object of substantial policy and investment attention, such as CCS-equipped thermal generation. Accordingly, the model focuses on a compact set of representative technologies (including coal and gas thermal plants, nuclear, hydro, solar PV, and onshore/offshore wind), while allowing new investments in CCS technologies from 2025 onwards. A central enabling output of the work is the construction of a simplified, aggregated dataset for Continental Europe to 2050 (Chapter 6), designed to preserve the main transition drivers while keeping the model computationally tractable.

To ensure that long-run trajectories originate from a technically grounded starting point rather than from an unconstrained mathematical least-cost dispatch, the thesis includes a dedicated 2024 baseline reconstruction and calibration phase (Chapter 5). A representative Reference Energy System (RES) for Continental Europe in 2024 is reconstructed using empirical data on installed capacities and electricity production consistent with the aggregated technology set used in the model. The model is then calibrated so that its base-year dispatch is coherent with the reconstructed reference mix, supported by complementary adjustments (e.g., Transmission and Distribution losses and efficiency coefficients) to ensure that electricity demand inputs translate consistently into generation requirements.

The model is configured to mirror the WEO 2024 scenario logic as closely as possible within a least-cost optimization framework and is run under three pathways aligned with WEO 2024 narratives: Stated Policies Scenario (STEPS), Announced Pledges Scenario (APS), and a Net Zero Emissions (NZE) pathway. Scenario differentiation is implemented primarily through electricity demand trajectories, evolving technology costs, fuel prices, carbon pricing, and, in the normative scenario, explicit emissions constraints. Across scenarios, the technology set is kept constant; what changes are scenario-specific assumptions and constraints governing deployment and transition dynamics. A key methodological point emphasized throughout the thesis is that a pure cost-minimization framework does not automatically reproduce the policy and feasibility constraints embedded in institutional scenarios. To partially bridge this gap, scenario-specific bounds are introduced to reflect deployment realism and transition pacing, including maximum annual investment levels and limits on year-to-year changes in electricity production by technology.

Original Contributions and Preview of Results

Results and interpretation are presented in Chapter 7. For RQ1, the thesis conducts a focused benchmarking exercise comparing OSeMOSYS outputs with WEO 2024 results for Continental Europe only where a direct, like-for-like comparison is feasible. Because WEO 2024 does not report regional emissions exclusively for the power sector, the benchmarking is restricted to electricity generation by source, which constitutes the most comparable indicator across the two frameworks. Moreover, owing to data availability constraints, the comparison is limited to STEPS and APS Scenario (detailed Continental Europe reporting is not available for the WEO 2024 NZE scenario). The benchmarking therefore focuses on sources that can be consistently aligned between the model and WEO reporting, most notably coal, gas, solar PV, wind, nuclear, and aggregated renewables, after harmonizing reporting conventions (including net-to-gross electricity alignment). Overall, the benchmarking shows that, despite its simplified structure, OSeMOSYS captures the aggregate 2050 outcome for Continental Europe with high robustness, especially once results are grouped into macro-categories. At the same time, the model exhibits non-negligible divergences along intermediate trajectories and at the level of single technologies, reflecting the fundamental difference between a deterministic, perfect-foresight least-cost optimizer (OSeMOSYS) and a policy-driven scenario framework (the GEC model underpinning WEO 2024).

Ultimately, these results underscore the broader relevance of this research. They provide evidence that open-source, simplified optimization models can serve as credible tools to extract long-term system-level insights for energy planning, particularly regarding end-state outcomes and macro-level trends, while also clarifying the conditions under which such models require complementary constraints and careful interpretation. Importantly, the analysis of the model results also provides an internal consistency check with the methodological conclusion of Chapter 1: outputs are sensitive to modelling choices such as temporal resolution, the single region/copperplate representation, the chosen modelling horizon, and assumptions on technology costs and deployment constraints. In addition, structural features of the OSeMOSYS formulation, most notably the absence of unit commitment constraints, the perfect foresight and the linear formulation affect technology-specific trajectories and intermediate-year patterns. This confirms, within the thesis' own modelling exercise, that model structure and inputs can be as influential as scenario narratives in shaping outcomes.

For RQ2, the cross-scenario analysis synthesizes the main trends emerging across the modelled pathways, including progressively deeper decarbonization as ambition increases, a structural shift in the role of dispatchable assets toward adequacy and flexibility provision, and the increasing importance of system flexibility as VRE penetration rises.

Finally, the thesis explicitly addresses a known limitation of long-horizon optimization, horizon effects and salvage value distortions, which can bias end-year investment incentives and distort "2050" outcomes. Chapter 8 explores these artefacts by extending the modelling horizon to 2070 and comparing 2050 vs. longer-horizon configurations, assessing how extended foresight affects investment decisions, the 2050 production mix, and emissions trajectories. Chapter 9 concludes by summarizing the findings, discussing limitations inherent to deterministic linear optimization and to the simplified aggregated representation of the European power system, and outlining methodological improvements and directions for future research.

Within this overall logic, the thesis provides four original contributions:

1. A structured benchmarking between a simplified, aggregated OSeMOSYS model and WEO 2024, delineating the conditions under which simplified tools yield robust macro-level insights versus where structural divergences occur. Notably, a systematic screening of academic databases, including ScienceDirect and Google Scholar, confirms a distinct research gap: no directly comparable benchmarking between OSeMOSYS and the WEO 2024 scenarios currently exists. Consequently, this thesis contributes pioneering

comparative evidence by aligning these frameworks under a consistent set of harmonized inputs,

2. The implementation and documentation of a reproducible modelling chain using the MUIO interface. A systematic screening of academic databases, including ScienceDirect and Google Scholar, confirms that this work constitutes the first documented application of MUIO to the Continental European power sector, thereby establishing a foundational reference setup for future research,
3. the construction of a new simplified, aggregated dataset for the Continental European power sector, structured for implementation in OSeMOSYS through the MUIO interface,
4. a synthesis of system-level trends characterizing the Continental European power sector's transition under increasing climate ambition, complemented by an original appraisal of end-of-horizon distortions. A systematic review of academic databases confirms a significant research gap: no OSeMOSYS-specific study explicitly addresses the interplay between horizon effects and salvage value mechanisms. This thesis fills that void by providing a dedicated analysis of their implications for the interpretation of 2050 outcomes.

1 Evolutionary Analysis of Global Energy Scenarios

This first chapter evaluates the accuracy of global energy and CO_2 emission projections formulated in the World Energy Outlook 2010 (WEO 2010) by comparing them with the actual historical time series (1990–2024) and the updated outlooks provided by the World Energy Outlook 2024. The analysis focuses on three fundamental variables at a global level, disaggregated by energy source: Total Primary Energy Demand (TPED), Total Electricity Production (TEP), and Total CO_2 Emissions.

The primary objective of this first chapter is to represent and compare the theoretical paths projected in 2010 against empirical historical data, thereby quantifying the deviations that have occurred over the past fourteen years. Furthermore, the chapter examines how these projections have been adjusted in the WEO 2024 framework, providing a clear overview of the current long-term expectations for the global energy transition. This comparative approach allows for a critical assessment of the evolution of projections accuracy. The chapter is structured as follows: after an initial overview of the International Energy Agency (IEA) and the specific contexts of the WEO 2010 and 2024, the methodology adopted for data alignment and comparison is detailed. Finally, the results are presented and discussed showing the gap between the 2010 projections and historical reality, while illustrating how these long-term pathways have been updated and recalibrated in the latest 2024 scenarios. This section highlights where the most significant deviations occurred and provides a clear overview of the current expectations for the global energy mix.

1.1. The International Energy Agency (IEA)

The International Energy Agency (IEA, 2026) is an autonomous Intergovernmental organization established in November 1974 with the aim of providing authoritative analysis, data, policy recommendations to member countries to maintain energy security, accelerate clean energy transition, achieve global net zero greenhouse gas emissions by 2050 and ensure energy access to all.

1.1.1. History and Shared Goals

Historical Foundation and Global Membership Expansion

IEA (IEA, 2026) was established is Paris under the 'Organization for Economic Co-Operation and Development' (OECD) as a response to the 1973-1974 oil crisis. In that period global oil prices reached very high levels due to the oil embargo imposed by major producers.

The initial goal of this new Agency was to provide oil supply security and policy cooperation between states, enhancing and favoring collective action to develop energy conservation policies.

Since its foundation, IEA has experienced a steady expansion of its membership (IEA, 2026). The founding members consisted of 17 nations: Austria, Belgium, Canada, Denmark, Germany, Ireland, Italy, Japan, Luxembourg, The Netherlands, Norway, Spain, Sweden, Switzerland, Türkiye, the United Kingdom, and the United States.

Over the following decades, the Agency grew significantly, including a broader range of economies and countries:

- 1976–1981: Greece (1976), New Zealand (1977), Australia (1979), and Portugal (1981).
- 1992–2008: Following the end of the Cold War and the acceleration of globalization, the Agency welcomed Finland and France (1992), Hungary (1997), the Czech Republic (2001), the Republic of Korea (2002), the Slovak Republic (2007), and Poland (2008).
- Recent Expansions: More recently, membership has expanded to include Estonia (2014), Mexico (2018), Lithuania (2022), and Latvia (2024).

Currently, nations such as Chile, Colombia, Israel, and Costa Rica are in the process of seeking full membership.

IEA with the 'Association program' collaborate now with Argentina, Brazil, China, Egypt, India, Indonesia, Morocco, Thailand, Singapore, South Africa, and most recently, Ukraine, which joined in 2022, and Kenya and Senegal, which joined in 2023.

Shared Goals and Net Zero Transition

This progressive expansion has transformed IEA first goal of assuring oil security to guarantee energy security in a climate-constrained world.

IEA members aim to create a policy framework coherent with the 'Shared Goals' (IEA, 2024):

- Advancing energy transition
- Ensuring energy security
- Promoting clean energy and secure supply chains
- Diversifying energy sources
- Increasing the efficiency of the energy system
- Maintaining open and transparent markets
- Advancing research, development and markets
- Advancing research, development and market deployment of new and improved energy technologies
- Putting people at the center of transitions
- Enhancing international collaboration
- Avoiding environmental impacts
- Providing accurate and granular data and statistics
- Applying shared values

Today, the IEA's mandate is defined by a multidimensional framework that aims to link the historical imperative of energy security with the urgent requirements of a clean global energy transition. At the core of the Agency's current mission there is the ambitious goal of achieving Net Zero emissions by 2050, a target designed to limit the global temperature increase to 1.5 °C from preindustrial levels through a transition away from fossil fuels that is described as 'just and equitable' (United Nations Climate Change, 2023).

To navigate this complex shift, the IEA promotes a strategy built upon three fundamental pillars. The first, technical resilience, focuses on enhancing energy efficiency, diversifying supply sources, and securing the supply chains of critical minerals, essential for clean technologies. This is complemented by a commitment to market integrity, ensuring that energy markets remain open and transparent during periods of structural change. Finally, the Agency emphasizes social equity, promoting people-centred transitions that prioritize job creation, inclusivity, and universal energy access.

1.1.2. Governance and Decision-Making Structure

The operational and strategic direction of the IEA is organized in a hierarchical governance structure, designed to ensure that technical analysis is integrated into political decision-making environment (IEA, 1999). The structure is organized in (IEA, 2026):

- The Governing Board: this board is the principal decision-making part of the organization and is composed of senior energy officials from each member country and it approves decisions regarding global energy development and Agency policies.
- The Ministerial Meeting: these meetings are held biennially, and this is the Agency's highest political forum, since energy ministers from member states joints. The Ministerial Meeting is responsible for setting the broad strategic mandates and long-term vision of the IEA. Ideas and policy directions developed during these meetings are subsequently submitted to the Governing Board for formal adoption.
- Standing Groups and Committees: these technical groups meet multiple times a year and are composed of experts and officials form member states and they focus on managing oil security, analyzing energy policy, trends and focus on the development and deployment of clean energy techs.

This internal architecture ensures that the IEA's analytical work is aligned with agency objectives and supervised by member states.

1.1.3. The IEA Publications

IEA provides several publications and reports on energy sources, technologies and regional dynamics for over 150 countries, becoming the world's leading authority on energy market analysis.

The Agency's outputs focus on multiple areas including policy recommendations, progress tracking, short-to-medium- term market forecast and long-term scenario modelling.

The key publications of IEA include several specialized reports beyond World Energy Outlook, that track the technological, financial and sectoral dimensions of the energy system.

The Net Zero Roadmap and Technology Perspectives

- Net zero by 2050 (IEA, 2026): A Roadmap for the Global Energy Sector: Published in 2021, this report defined the first comprehensive pathway to reach global carbon neutrality. In the report a normative roadmap is established to maintain energy security and economic growth while eliminating emissions.

- Energy Technology Perspective (IEA, 2024): This is a biennial publication focusing on the status and future of clean energy technologies. It is a technical report for policymakers, analyzing the maturity, supply chains, and deployment challenges of emerging energy solutions.
- Tracking Clean Energy Progress (IEA, 2024) : This framework monitors critical energy technologies and sectors, assessing whether their current development speed aligns with the requirements of the Net Zero scenario.

Market Reports and Sectoral Analysis

IEA provides regular monitoring of global commodity markets.

- Oil (IEA, 2026), Gas (IEA, 2026), and Electricity (IEA, 2025) Market Reports: These publications (issued monthly, quarterly, or annually) offer detailed forecasts for demand, supply, and trade flows. They track the impact of geopolitical events and economic cycles on price volatility and system reliability.
- Global EV Outlook (IEA, 2025): A specialized annual review of electric mobility, combining historical sales data with projections for charging infrastructure and battery materials.
- Renewable Energy Market Update (IEA, 2025): Tracks global renewable capacity additions and biofuel demand, highlighting the policy implications that drive or hinder renewable developments.

Cross Cutting Reports: Investment and Efficiency

- World Energy Investment (IEA, 2025): This annual report tracks capital flows across the entire energy sector, analyzing how investors evaluate risks and opportunities in fossil fuels versus clean energy, critical minerals, and R&D.
- Energy Efficiency Report (IEA, 2025)**:** This report evaluates progress in buildings, transport, and industry, and the role of efficiency in reducing the overall scale of the energy system.

Institutional Accountability: Country Reviews

The IEA has conducted in-depth Energy Policy Reviews (OECD, 2024) for its member and association countries. These periodic peer reviews assess the full spectrum of a nation’s energy system and its alignment with climate goals, ensuring that national-level policies are transparent and coherent with IEA standards.

1.2. The World Energy Outlook Framework

Overview and Historical Context

The World Energy Outlook (WEO) is the International Energy Agency's (IEA) most important and popular publication, focusing on global energy projections and analysis. The first WEO was published in 1994 and from 1998 it became an annual publication (Bamberger, 2003).

In the report several topics are discussed. Medium-to-long energy market projections, analysis and data regarding energy demand, energy consumption, electricity generation and consumption, total installed electrical capacity as well as total CO_2 emissions and economic and activity indicators both worldly and regionally. There are also further datasets in the annexes of WEOs including regional historical and projected data for Oil, Natural Gas and Coal production and demand, total energy supply and electricity generation per source, total final consumption by sector (industry, transport and buildings), total carbon dioxide emissions and consumption by sectors.

Scenario Architecture

The World Energy Outlook uses three scenarios to examine future energy trends. Generally, there is a normative scenario, designed to achieve a specific outcome, that shows the pathway to reach it, and two exploratory scenarios. In these two exploratory scenarios a set of starting conditions are defined and then is analyzed where they lead based on model representations of the energy system.

A critical distinction must be made between deterministic forecasts and the scenario-based approach adopted by the IEA. The scenarios presented in the World Energy Outlook are not intended to be predictions of a single, definitive future. Instead, they serve as rigorous analytical tools that allow policymakers, investors, and researchers to explore various "if-then" trajectories.

Analyzing these scenarios, it is possible to compare different possible versions of the global energy future and identify the specific levers and actions, such as policy shifts, carbon pricing, or technological deployment, that lead to them.

The Modelling Framework

The IEA results and the projections presented in the World Energy Outlook are the product of a sophisticated modelling framework that has evolved from the earlier World Energy Model (WEM) into the current Global Energy and Climate (GEC) Model. In the following sections WEM and GEC Model will be further analyzed.

Data Categories and Inputs

The results of the modelling process are obtained starting from an enormous volume of data, required to calibrate the model. These inputs can be categorized into four main blocks:

1. Policy & Regulatory Data: Extracted from the Policies and Measures Database (PAMS), including existing laws, announced pledges (NDCs), and international agreements.
2. Macroeconomic Drivers: projections of GDP and population growth, urbanization rates, and industrial activity levels.
3. Technological & Cost Parameters: Data on technology maturity and cost-reduction curves, specifically the Levelized Cost of Electricity (LCOE) for renewables, battery learning rates, and R&D investment trends.
4. Geological & Market Data: Estimates of fossil fuel reserves, the availability of critical minerals (Lithium, Copper, Cobalt), and current energy price trends across global markets.

Primary Objectives and Aims

The primary objective of the WEOs is not to predict the future, but to provide a rigorous analytical framework for understanding the global energy system. In particular, the aims of these publications include:

- Supporting decision-making: they provide useful insight and information for policymakers and energy investors to guide energy planning and capital allocations.
- Identification of energetic trade-off: they allow to explore trade-offs between energy security, economic affordability and environmental sustainability.
- Path defining: they define the path required to reach specific climate targets.
- Risk assessment: Alerting the global community to potential gaps between current policy trajectories and long-term climate goals.

Evolution of the Reporting Framework

It is important to emphasize that between the earlier editions of the World Energy Outlook and the most recent publications, the IEA reporting framework has undergone a huge evolution.

There are several discrepancies between different editions, including:

- Variable Nomenclature and Metrics: Significant shifts in terminology have occurred, most notably the transition from Total Primary Energy Demand

(TPED) to Total Energy Supply (TES), alongside a shift in standard units from Million tonnes of oil equivalent (Mtoe) to Exajoules (EJ).

- Computational Methodology: The mathematical logic for calculating energy balances and CO_2 emission factors has been updated to align with the latest IPCC standards and scientific knowledge.
- Technological Granularity: Modern editions feature a much higher resolution of data regarding clean energy technologies (such as green hydrogen, battery storage, and critical minerals) which were either absent or highly aggregated in older reports.
- Geographical and Regional Re-aggregation: The definition of world regions and the boundaries of emerging economies have been frequently adjusted to reflect shifting geopolitical realities, requiring careful re-alignment for consistent longitudinal analysis.
- Scenario Architectures: The actual group of scenarios utilized by the IEA has been frequently replaced and redefined to reflect new political realities. For instance, the 2010 framework was built around the Current Policies, New Policies, and 450 scenarios. Instead, the 2024 framework is based on the Stated Policies Scenario (STEPS), the Announced Pledges Scenario (APS), and the normative Net Zero Emissions by 2050 (NZE) pathway. Each change represents a different set of assumptions regarding the speed of implementation of global policy and climate ambition.
- Evolution of the modelling tools: Since 1993, the IEA has experienced a continually evolving set of modelling tools. In 2021, the IEA adopted the Global Energy and Climate Model that is now the principal tool used to generate detailed sector-by-sector and region-by-region long-term scenarios for the World Energy Outlook and other IEA publications.

Methodological Implications for Analysis

Ultimately, these systemic discrepancies and differences between different editions preclude a direct comparison of the datasets.

Consequently, the harmonization and recalibration efforts detailed in the following methodology section (such as the Overlap Approach for emissions and unit conversion for energy demand) are essential prerequisites for a transparent and statistically valid analysis and data retrieval.

1.3. Focus on the World Energy Outlook 2010

The World Energy Outlook 2010 (IEA, 2010) analyzed the global energy system in a period when the world was emerging from the financial and economic crisis of

2008–2009 and was facing growing concerns about energy security, affordability, and climate change. The report highlights that, despite the temporary slowdown caused by the crisis, global energy demand was expected to resume to growth, driven mainly by emerging economies, such as China and India, due to faster growth rates for economic activity, industrial production, population and urbanization.

Global demand for each fuel source was projected to increase, with fossil fuels accounting for over one-half of the increase in total primary energy demand. Fossil fuels were projected to remain dominant in the global energy mix for decades, with coal demand rising rapidly and oil demand continuing to grow, especially in the transport sector and remaining the dominant fuel. The Outlook stresses that existing energy policies at the publication time were insufficient to place the world on a sustainable path, leading to increasing greenhouse gas emissions and the growing risk of severe climate impacts.

A clear outcome of the report is that the only way of having a near peak in oil production is due to policies. But if governments do nothing, demand will continue to increase, supply costs will rise, the economic burden of oil use will grow, vulnerability to supply disruptions will increase and the global environment will suffer serious damage. WEO underlines also the future role of unconventional oil through 2035, because even if is more costly than the conventional one, resources are several times more abundant. Also, natural gas and LNG are expected to play a central role as energy sources especially in China.

A central message of the WEO 2010 is the scale of investment required to meet rising energy demand while maintaining reliable supply: massive and sustained investment in upstream oil and gas, power generation, and energy infrastructure are needed to avoid supply bottlenecks and price volatility. At the same time, the report underscores the vulnerability of energy-importing countries to high and volatile fossil fuel prices, highlighting energy efficiency as one of the most cost-effective and immediately available tools to improve energy security and reduce emissions.

Electricity demand was expected to grow rapidly, requiring large additions of power generation capacity, much of which was projected to come from coal and natural gas in the absence of stronger climate policies.

While renewable energy and low-carbon technologies were gaining attention, their deployment was still relatively limited and highly dependent on policy support. The future of renewables, especially in the power sector, depends on government support, even if they are expected to become increasingly competitive as fossil fuel prices rise and the renewable technology become mature.

This edition of WEO 2010 underlines also the role of the Caspian region in ensuring energy security in the rest of the World by increasing the diversity of oil and gas supply thanks to their resources.

The WEO 2010 places strong emphasis on the long-term risks of delaying action on climate change, introducing the 450 Scenario to illustrate how early and coordinated policy action could limit the increase in global temperatures, reduce future costs, and avoid locking in carbon-intensive infrastructure. In addition, in the report it is shown that removing fossil-fuel consumption subsidies, which accounted for 312$ billion in 2009, could be useful to meet energy-security and environmental goals, including mitigating CO_2 and other emissions.

Overall, the report conveys a sense of urgency: decisions taken in the following decade would shape the energy system for many years, and continued reliance on fossil fuels without stronger policy intervention would increase environmental risks, deepen energy security concerns, and ultimately raise the economic cost of transitioning to a more sustainable energy system.

1.3.1. The WEO 2010 Scenario Framework

In this edition of the World Energy Outlook (IEA, 2010) three different scenarios are presented, and they mainly differ according to underlying assumptions about government policies. Each scenarios projects until 2035 the explored variables of Total Primary Energy Demand (Mtoe) of different sources, Total Electricity Production (TWh), Total Installed Capacity (GW), Total CO_2 Emissions (Mton) for both World and regions analyzed in the report.

Current Policies Scenario

The first exploratory scenario modelled in WEO 2010 is the 'Current Policies Scenario' and it is defined as the baseline or reference case, and it is equivalent to the 'Reference Scenario' published in previous edition. This scenario considers exclusively policies and regulations that were formally adopted by countries by mid-2010. This baseline scenario provides the benchmark for the direction of the global energy system in the absence of additional political interventions.

New Policies Scenario

The second exploratory scenario modelled is the 'New Policies Scenario' and it is introduced for the first time in this 2010 edition and this scenario incorporates both policy commitments and national pledges that were announced but not yet fully implemented by 2010. In addition, in this scenario fossil-fuel subsidies are completely phased out in all net-importing regions by 2020 and in net-exporting regions where specific policies have already been announced.

450 Scenario

The last scenario modelled is the ambitious ‘450 Scenario’ that is a normative pathway. The primary objective of this scenario is to limit the atmospheric concentration of greenhouse gases to 450 ppm of CO_2 equivalent. This emission limit was computed as the necessary threshold to keep and limit the global temperature increase within 2° C from preindustrial levels. This scenario is supported by near-universal removal of fossil-fuel consumption subsidies and assumed the full implementation of high-end national pledges and the adoption of significantly stronger policies after 2020. In this scenario, fossil fuel subsidies are completely phased out in all net importing countries by 2020, and in all net exporting countries by 2035, except Middle East where it is assumed that the average subsidization rate declines to 20% by 2035.

1.3.2. World Energy Model (WEM)

Introduction to the World Energy Model (WEM)

The results presented in the World Energy Outlook are obtained from the World Energy Model (IEA, 2018), that is a model that integrates energy supply, energy transformation and energy demand, with the aim of representing and replicating how energy market functions. WEM is defined as a partial equilibrium simulation model, a dual classification that explains both its economic and mathematical approach.

- Partial Equilibrium: Unlike General Equilibrium models that simulate the entire global economy and the interdependencies between all sectors, the WEM focuses specifically on the energy sector. It clears energy markets by balancing supply and demand for energy services, while considering broader macroeconomic drivers, such as GDP growth, demographic trends, and international trade, as exogenous inputs. The model calculates how energy demand adapts to economic growth, but it does not simultaneously recalculate how energy prices might alter that economic growth in a feedback loop.
- Simulation: As a simulation tool, the WEM is designed to replicate the behaviour of energy consumers and producers under specific conditions. Rather than searching for a single "optimal" mathematical solution the WEM uses "if-then" logic. It projects how the energy system evolves based on current policies, historical trends, and technological maturity. This approach is particularly effective for "what-if" analysis, allowing the IEA to illustrate how different policy frameworks or market signals could realistically shape the future energy landscape.

Modular Structure and Functional Blocks

The model is articulated in three main modules covering final energy consumption (including industry, transport, buildings, agriculture and non-energy use), fossil fuel and bioenergy supply, and energy transformation (including power and heat generation, oil refining and other transformations).

Geographical Coverage and Regional Resolution

The model in 2010 covers the following regions/countries (IEA, 2010): World, OECD, OECD North America, the United States, OECD Europe, the European Union, OECD Pacific, Japan, non-OECD, Eastern Europe/Eurasia, the Caspian, Russia, non-OECD Asia, China, India, the Middle East, Africa, Latin America and Brazil.

Model Outputs and Results

The outputs that can be obtained from the model include, for the different regions covered, energy demand and supply by fuel, investment needs, CO_2 emissions and end-user prices.

Technology Selection and Market Share Allocation

The model's primary objective is to determine the most viable share of alternative technologies required to satisfy global energy service demand while ensuring a balanced energy system. In addition, while the WEM is fundamentally built as a simulation model, the selection of technologies is driven by a cost-based logic. The model determines the market share of various technologies in satisfying energy service demand based on their relative cost-competitiveness. Moreover, in different segments of the model the Logit and Weibull functions are used to allocate the share of technology based upon their specific cost. These functions allow the model to simulate realistic technology adoption rates by weighing specific costs against one another. The specific costs include the investment costs, the operating and maintenance costs, fuel costs and emissions costs.

Exogeneous Assumptions and Input Data

The main exogenous assumptions and input to the model concern economic growth, demographics, technological performances and developments as well as fuel prices, with the latter that are treated both as inputs and outputs of the modelling process.

The model for running simulations requires annual data, taken from IEA's own databases, regarding costs of CO_2 emissions, plans and measures for energy and climate policies, technological progress by industry and region, and assumptions for macroeconomic and demographic developments (i.e., economic growth).

Key Purposes and Application of WEM

WEM model is used for the following purposes:

- Analyze trends in demand, supply availability and constraints, international trade and energy balances by sector and by fuel in the projection horizon.
- Analyze the environmental impact of energy use.
- Analyze the impact of a range of policy actions and technological developments on energy demand, supply, trade, investments and emissions.
- Evaluate investment in the energy sector.

Core Model Blocks

The model is organized in three main model blocks, as shown in Figure 1.1:

- Energy Supply
- Energy Transformation and Conversion
- Energy Demand

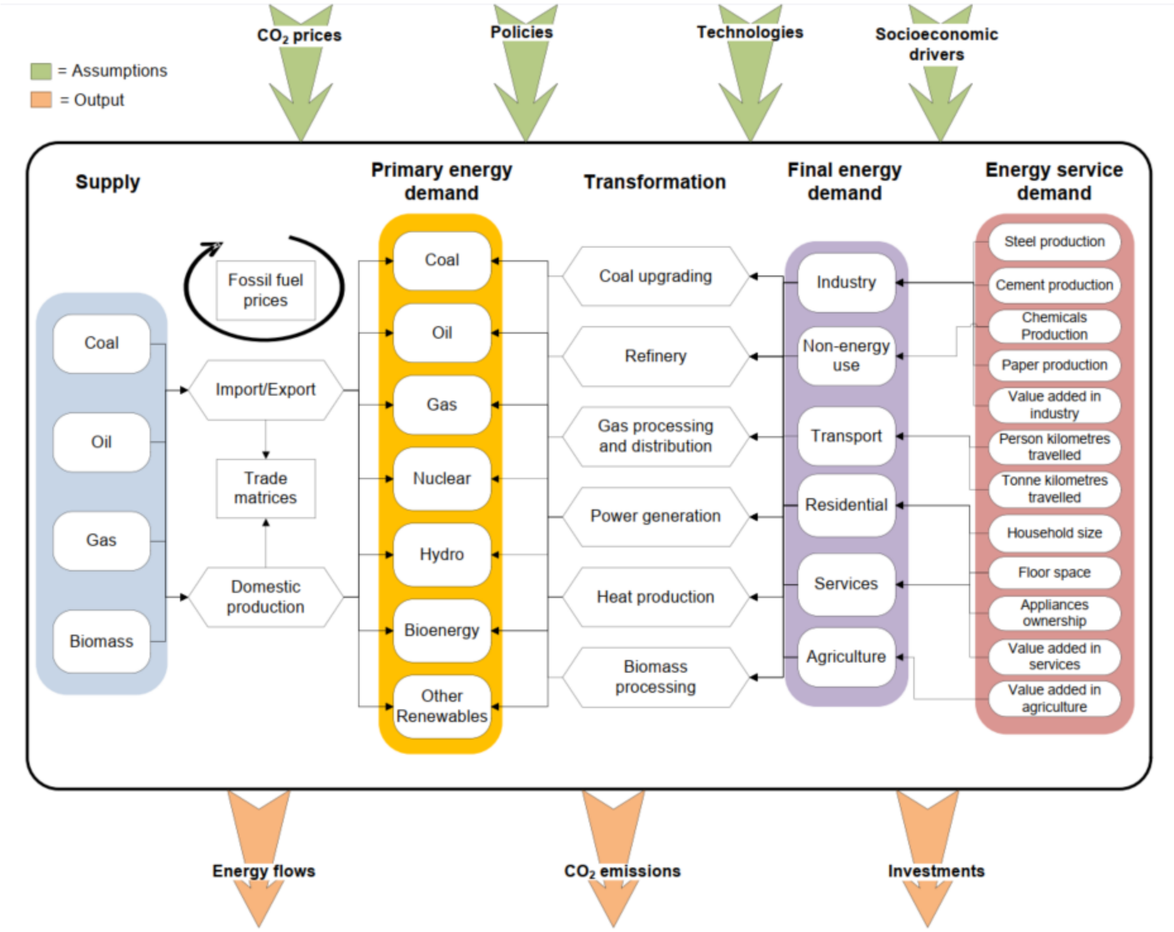

Figure 1.1: World Energy Model Overview (IEA, 2018)

Internal Logic and Interconnections

Figure 1.1 illustrates the internal logic of the World Energy Model by showing the interconnections and links between energy service demand drivers, final energy demand, conversion/transformation processes, and energy supply.

Socioeconomic Drivers and Service Demand

In the model structure, socioeconomic drivers enter the modelling framework as exogenous inputs and represent the starting point of the energy system simulation. Variables such as population growth, economic development, income levels, urbanization levels, and mobility needs determine the level of sectoral economic activity and the demand for energy services in each region covered. These service demands, that are energy demand drivers, are then translated into final energy demand through assumptions on energy intensities, end-use technologies (this is another exogenous input), and efficiency improvements.

Conversion Processes and Primary Energy Requirements

This final demand is not satisfied directly by primary energy but is first allocated to a set of energy conversion processes, such as electricity and heat generation, refining, and fuel transformation. Each conversion process requires specific energy inputs, and the aggregation of these inputs defines primary energy demand by fuel type. Primary demand then drives the supply module, where domestic production, international trade, and price formation for energy commodities are determined to balance demand.

The Role of Energy and Climate Policies

In the model structure, energy and climate policies represent a second category of exogenous inputs and affect the energy system at multiple stages, as illustrated in Figure 1.1. On the demand side, policies influence final energy consumption through efficiency standards, electrification targets, and fuel-switching measures in end-use sectors. At the conversion stage, policy assumptions define and influence the technology mix and performance of power generation, refining, and other transformation processes by imposing capacity constraints, technology deployment targets, or phase-out schedules. On the supply side, policies affect production and trade by modifying cost structures through carbon pricing, taxes, and subsidies, as well as by constraining resource availability.

Policy Impact and Sequential Propagation

Unlike socioeconomic drivers, which determine the level of energy service demand, energy policies primarily influence the technological and fuel choices used to meet that demand, thereby affecting primary energy demand, emissions, and investment outcomes. Exogenous assumptions, such as energy and climate policies, CO_2 prices, and technological progress, enter the system at multiple points, influencing sectoral demand, conversion efficiencies, fuel choices, and supply costs. The arrows in the figure therefore represent a sequential and consistent propagation of assumptions from economic activity to final demand, from final demand to primary energy requirements, and ultimately to supply decisions and emissions outcomes.

Iterative Balancing and Output Generation

Ultimately, WEM functions as a partial-equilibrium model that iteratively balances supply and demand through price feedback, providing as outputs total energy flows, required infrastructure investment, and resulting CO_2 emissions.

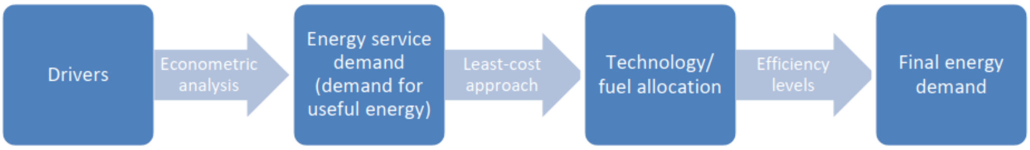

Figure 1.2: General Structure of Demand Modules (IEA, 2018)

Demand Module Structure and Least-Cost Approach

Figure 1.2 explains how the World Energy Model translates the socio-economic drivers into final energy demand through a demand-driven logic.

Exogenous socioeconomic drivers such as population, GDP, economic structure, and activity indicators are converted, through econometric analysis, into energy service demand, defined as the demand for useful energy (e.g. passenger-kilometers, heated floor space, or industrial output). The model then applies a least-cost approach allocating technologies and fuels capable of delivering these services, considering technology costs, fuel and carbon prices, policies, and other constraints. Given the selected technologies, efficiency levels determine the amount of final energy required to provide each unit of useful energy.

1.3.3. Key Input and Assumptions in WEO 2010

There are several underlying macroeconomic assumptions that are used to calibrate the different scenarios of the model for the 2010 edition.

The projections in the WEO 2010 are obtained starting from a set of 'exogeneous drivers' regarding the demographic, technological and economic assumptions, sourced in (IEA, 2010). These assumptions, with the except for energy prices and technology development, are the same for each scenario, ensuring that the differences between scenarios are driven only by policy choices rather than varying socioeconomic backgrounds.

Demographic and Economic Growth

- Global population was projected to grow from 6.7 billion in 2008 to 8.5 billion by 2035, representing an average annual increase of 1%. This growth was characterized by two structural trends: it occurred predominantly in non-OECD countries and was heavily concentrated in urban centers, factors that typically correlate with higher per capita energy intensity. This assumption is based on projections by the United Nations. The global population estimate for the year 2035 assumed in the WEO 2010 was subsequently revised upward in the WEO 2024, increasing from 8.5 billion to 8.85 billion.

- Economic activity was assumed to grow at an average annual rate of 3.2% (2008–2035). While the global economy suffered a 0.6% contraction in 2009 due to the Great Recession, the model assumed a rapid rebound of 4.6% in 2010, with India, China, and the Middle East maintaining their roles as the principal drivers of global economic expansion. Moreover, it is important to underline how economic activity is the principal driver of energy demand and the output of the WEO are very sensitive to GDP variations. Energy demand tends to grow in line with GDP, but at a lower rate. Historical records show an average annual GDP growth rate of 3.0% between 2011 and 2023. For the subsequent 2023–2035 period, the WEO 2024 assumes a nearly identical average growth rate of 3.1%.

Energy Prices

Energy prices assumptions in WEO 2010 are scenario-dependent, due to the feedback loop between policy-driven demand and supply-side production cost. It is important to underline how fuel prices (oil, gas, coal) are treated both as inputs and outputs of the modelling process. In fact, starting from an initial price trajectory, the final price is defined through an iterative equilibrium process, assuring consistency between supply and demand. The international prices for coal, gas, and oil have to be set at levels that are sufficient to trigger the investment needed to supply the quantities of fossil fuels required by projected demand.

The model starts from an initial price assumption for coal, gas, and oil. Given these prices, the supply modules estimate how much production can be brought to market, considering the costs of different supply options and limits on how fast production can increase. If this level of supply is not sufficient to meet global demand at the assumed prices, the model increases prices and feeds them back into the system. Energy demand is then recalculated using the updated prices, and the new demand levels are again passed to the supply modules. This process is repeated until supply and demand are balanced for each year of the projection horizon.

The resulting price trajectories are smooth because the WEM model focuses on long-term equilibrium conditions, while real-world fossil-fuel prices are typically more volatile and cyclical in the short term. In particular:

- Crude Oil: In the New Policies Scenario, the IEA crude oil import price was projected to reach $113/barrel by 2035 (in 2009 dollars). Prices were assumed to be higher in the Current Policies Scenario due to unconstrained demand, while the 450 Scenario experienced lower prices resulting from a significant shift away from petroleum. In the WEO 2024, crude oil prices for the year 2030 are estimated at $79, $72, and $42 per barrel in the STEPS, APS, and NZE scenarios, respectively. These figures represent a downward revision compared to the projections originally established in the WEO 2010.

- Natural Gas: Prices were assumed to remain low relative to oil, particularly in North America, due to the unconventional gas (shale gas) revolution. However, a gradual price convergence between North American, European, and Asia-Pacific markets was expected as production costs for new reserves increased.
- Coal and Carbon: Coal prices remained the most stable across scenarios, decreasing in 450 Scenario due to carbon and emission constraints. Crucially, the 2010 framework anticipated the expansion of CO_2 trading schemes, with carbon prices rising progressively in both the New Policies and 450 Scenarios to penalize carbon-intensive generation. Specifically for the European Union, the WEO 2010 New Policies scenario estimates a carbon price of $38/t in 2020 and $50/t in 2035. Under the Current Policies scenario, these projections are lower, at $30/t and $42/t, respectively, while the more ambitious 450 Scenario anticipates prices of $45/t in 2020 and $120/t in 2035. Historically, however, the actual EU carbon price has fluctuated between 16 and 33 EUR/t during the 2020 period (Tradings Economics, s.d.). In a significant upward revision, the WEO 2024 assumes much higher values for the EU by 2035. The price is projected at $145/t in the Stated Policies Scenario (STEPS), $160/t in the Announced Pledges Scenario (APS), and $180/t in the Net Zero Emissions (NZE) scenario. This drastic increase in the carbon price floor reflects a fundamental shift in policy ambition and the structural strengthening of the EU Emissions Trading System (ETS) compared to the assumptions made over a decade ago.

To obtain post-tax prices faced by end users, the model incorporates excise taxes, value-added tax rates, and subsidies in the international fuel prices. Excise taxes and VAT rates on fuels are assumed to remain constant throughout the projection horizon, while energy-related consumption subsidies are assumed to be gradually reduced over time, at different rates depending on the region and the scenario considered.

Technology

Technology assumptions in WEO 2010 are also scenario dependent. Projections are very sensitive to assumptions about development in technology and how quickly new technologies are deployed. Government policies and support, energy prices, regulatory measures, direct public-sector investment have an important impact on the pace of development and deployment of new technologies. Consequently, more rapid technological advances are seen in the 450 Scenario.

Moreover, policies are the main driver for technological developments and deployment, and for this reason the slowest technological change is experienced in the Current Policies Scenario, because no new public policy actions are assumed. Yet, even in this scenario, significant technological improvements occur, aided by higher energy prices.

It is important to underline that a conservative technological approach is used in this edition, since IEA explicitly assumed that no entirely new or unknown technologies would be deployed before the 2035 horizon. The model relied exclusively on technologies that were already known or in the early stages of commercialization in 2010.

Policies

Policies included in World Energy Outlook 2010 differ according to the scenario. The Current Policies Scenario includes all policies in place and supported through enacted measures as of mid-2010. Instead, the New Policies Scenario considers all policies and measures included in the Current Policies Scenario and assumes:

- a caution implementation of the Copenhagen Accord commitments by 2020,
- the persistence of the European Union Emission Trading System and the extension of a cap-and-trade system in the rest of the OECD countries after 2020,
- phase out of fossil-fuel consumption subsidies in all net-importing regions by 2020 (and, as in the Current Policies Scenario, in net-exporting regions where specific policies have already been introduced),
- extension of nuclear plant lifetimes by 5 to 10 years with respect to the Current Policies Scenario, on a plant-by-plant basis,
- for 2020-2035, additional measures that maintain the pace of the global decline in carbon intensity already introduced for the period 2008-2020.

Instead, the 450 Scenario consider all the policies already included in the New Policies Scenario, strengthened and extended, with the addition of the following:

- implementation by 2020 of the high-end of the range of the Copenhagen Accord commitments, since many countries in the definition of the Copenhagen Accord did not consider a single fixed number of emissions reductions, but a range.
- cap-and-trade systems in the power and industry sectors, from 2013 in OECD+ countries and after 2020 in Other Major Economies,

- international sectoral agreements for the iron and steel, and the cement industries.
- international agreements on fuel-economy standards for passenger light-duty vehicles (PLDVs), aviation and shipping.
- national policies and measures, such as efficiency standards for building,
- the complete phase-out of fossil-fuel consumption subsidies in all net-importing regions by 2020 (at the latest) and in all net-exporting regions by 2035 (at the latest), except for the Middle East where it is assumed that the average subsidization rate declines to 20% by 2035.
- extension of nuclear plant lifetimes by 5 to 10 years with respect to the New Policies Scenario, on a plant-by-plant basis.

There are also other sectors and regional specific policies reported in the Annex B of the WEO 2010 (IEA, 2010).

1.4. Focus on the World Energy Outlook 2024

The World Energy Outlook 2024 (IEA, 2024) aims to analyze the evolution of the global energy system in a context characterized by several and persistent geopolitical tensions, accelerating climate changes and rapid but uneven technological transformation toward greener and cleaner energy sources. Recent events, including the war in Ukraine and instability in the Middle East, have shown how quickly energy dependencies can become vulnerabilities, reminding policymakers the importance of energy security and energy independence. At the same time, the concept of energy security is evolving, it is no longer depending only on the availability of oil, gas, and coal, but it is increasingly depending on the reliability of electricity systems and on resilient supply chains for clean energy technologies (critical minerals), which are often highly concentrated in a small number of countries.

The report highlights how transition to clean energy is increased in recent years, driven by government policies, industrial strategies, and falling costs of clean energy technologies.

The report also showed that investment in clean energy is now approaching two trillion dollars per year, renewable capacity additions have reached record levels (+560 GW of new renewables in 2023), and technologies such as solar photovoltaics, batteries, and electric vehicles are expanding rapidly.

However, this progress is uneven across regions. While China accounts for a very large share of new clean energy deployment, many emerging and developing economies struggle to attract investment because of high financing costs, regulatory uncertainty, slow permitting processes, and insufficient electricity networks, continuing to rely on fossil fuel as primary power generation source.

A key result of the Outlook is that global energy markets are entering a new phase, characterized by higher supply of both fossil fuels and clean energy technologies. Oil and liquefied natural gas markets are expected to face periods of oversupply in this decade, while manufacturing capacity for solar panels and batteries is expanding faster than demand. This creates strong competition and downward pressure on prices, which can benefit energy-importing countries but also increase uncertainty for producers and investors.

Another key concept is related to electricity, since it is growing much faster than overall energy demand. This is due to the electrification in industry and transport, the rise of demand for cooling as temperatures increase, and the expansion of data centers and digital technologies. As a result, power systems face growing challenges related to flexibility, grid expansion, and resilience, especially due to the more frequent extreme weather events.

The Outlook also examines how the rapid growth of electric vehicles is changing the oil market by slowing down the increase in global oil demand. Because demand is growing more slowly, oil supply is now growing faster than consumption. This shift forces oil producers to compete more for market share and leaves a larger part of their production capacity unused. Ultimately, this surplus of oil leads to lower prices in the global market.

At the same time also the future of natural gas is uncertain. A large amount of new LNG export capacity is expected to enter the market, but it has to compete with cheap renewable electricity, especially in power generation.

Although lower fossil fuel prices can reduce energy costs for consumers and improve industrial competitiveness in importing regions, they may also weaken incentives to improve energy efficiency and investments in cleaner technologies, potentially slowing the pace of structural change in the energy system.

Overall, the WEO 2024 concludes that current trends and efforts to achieve a clean energy transition are still not sufficient to meet global climate goals. Emissions remain high, and the world is not yet on a path consistent with limiting global warming to internationally agreed targets. Accelerating progress will require not only faster deployment of clean technologies, but also greater investment in electricity networks, storage, energy efficiency, and system resilience, as well as stronger international cooperation and support to ensure that developing economies can fully participate in the transition, guaranteeing that modern energy services are expanded in an equitable way.

1.4.1. The WEO 2024 Scenario Framework

The World Energy Outlook 2024 (IEA, 2024) through the definition of three scenarios provides a comprehensive framework for understanding the future of global energy. Each scenario originates from the same baseline, incorporating the latest data on energy supply, demand, market trends, and technology costs, while assuming similar trajectories for global population and economic growth. These scenarios are not deterministic forecasts; rather, they serve as “if-then” explorations of how different policy choices and investment strategies impact energy security and emissions. The analysis identifies three distinct scenarios, each providing projections up to 2050 for the key variables under study. These include Total Primary Energy Demand, broken down by energy source, as well as Total Electricity Production, Installed Capacity, and Total CO_2 Emissions. These metrics are analysed at both global level and for the specific regions covered by the model.

The scenarios implemented are:

- Stated Policies Scenario (STEPS): Exploratory scenario that reflects the current situation, based on existing policy settings and announced industrial goals. It accounts for energy, climate and related industrial policies that are in place or that have been announced. The STEPS is currently associated with a global temperature rise of approximately 2.4 °C by 2100 from preindustrial levels.
- Announced Pledges Scenario (APS): Exploratory scenario that assumes that all national energy and climate targets, including long-term Net Zero pledges and Nationally Determined Contributions (NDCs), are met in full and on time. It serves as a measure of the “ambition gap” between current policies and stated goals. The APS is associated with a temperature rise of 1.7 °C by 2100.
- Net Zero Emissions by 2050 (NZE) Scenario: Normative scenario that illustrates a pathway to achieve global carbon neutrality by mid-century, consistent with limiting warming to 1.5 °C. It also targets specific UN Sustainable Development Goals (SDGs), such as universal energy access by 2030.

In addition, to account for uncertainties, the core scenarios are often accompanied by sensitivity cases that explore different outcomes, such as the pace of electric vehicle adoption, the speed of renewable deployment, and fluctuating electricity demand from emerging sectors like data centers.

1.4.2. Global Energy and Climate (GEC) Model

Evolution of IEA Modelling Tools

Among the different editions of WEOs the IEA has used a continually evolving set of detailed, world-leading modelling tools.

First, the World Energy Model (WEM), a large-scale partial equilibrium simulation model designed to replicate how energy market's function was developed. Then IEA developed the Energy Technology Perspectives (ETP) model, a technology-rich bottom-up model, used for other publications.

In 2021 IEA introduced a new hybrid model, the GEC model, joining the strengths and potentialities of both the models in one integrated modelling framework, that is used from that year onward as the principal tool to generate detailed sector-by-sector and region-by-region long-term scenarios across IEA's publications.

Core Characteristics of the GEC Model

The GEC model is a large-scale, bottom-up, partial-equilibrium simulation modelling framework with elements of optimisation (IEA, 2024).

- Bottom-up: GEC is based on a highly disaggregated database of technologies. It accounts for thousands of specific technologies (e.g., types of wind turbines, industrial boilers, electric vehicle categories) to build the energy system from the ground up.
- Partial Equilibrium: As discussed, it focuses on the energy sector. It ensures that supply and demand meet for each energy carrier, but it takes external (exogenous) inputs for the wider economy, such as GDP and population.
- Partial Optimization: The GEC is not a "pure" optimization model for the whole system. Instead, it uses optimization specifically for certain sectors, most notably the Power Sector and parts of the Industrial Sector. Other sectors, like transport or buildings, often rely more on simulation to better reflect real-world consumer behaviour and policy constraints.

Model Objectives and Modular Structure

Its primary purpose is to evaluate energy supply and demand, as well as the environmental impacts of energy use and the impacts of policy and technology developments on the energy system.

It is organized in three modules, dynamically soft linked, that include:

1. Final energy demand, covering industry, transport, buildings, agriculture and other non-energy use, driven by detailed modelling of energy service and material demand.
2. Energy transformation, including electricity generation and heat production, refineries, the production of biofuels, hydrogen and hydrogen-based fuels and other energy-related processes, as well as related transmission and distribution systems, storage and trade.
3. Energy supply, including fossil fuels exploration, extraction and trade, and the availability of renewable energy resources.

Input and Decision-Making Logic

The GEC model is driven by exogenous input such as economic and demographic growth, and technological advancements. It employs econometric estimations and detailed stock accounting of existing infrastructure (such as industrial capacity and vehicle fleets) to project energy service demand. This demand-driven approach determines the necessary fuel transformations and primary energy requirements, utilizing cost-minimization functions, including Logit and Weibull distributions, to calculate the market share of specific technologies based on investment, operating, and fuel costs. Rather than following a purely theoretical least-cost pathway, the analysis incorporates real-world constraints like market failures, political preferences, and capital limitations to reflect sectoral realities.

Integrated Structure

Figure 1.3 illustrates the structural logic of the GEC Model, that operates as an integrated loop connecting the three modules.

The framework starts at the top with the Energy Service and Material Demand where socioeconomic drivers, historical technology stocks, and specific policies are used as inputs to define the required services for the industry, buildings, transport, and agriculture sectors. This demand-side assessment determines the necessary energy services which are then translated into specific fuel and electricity requirements.

Supply, Transformation and Price Feedback

These requirements flow downward into the Transformation Sector, where the system simulates the conversion of raw resources into usable energy through processes like electricity generation and heat production, refineries for liquid fuels, and the production of biofuels and hydrogen-derived fuels.

At the base of the model lies the Primary Energy Supply, representing the global extraction and harvesting of oil, gas, coal, renewables, and nuclear power. The entire system is harmonized by a central feedback loop mechanism where prices act as the primary intermediary to balance supply and demand.

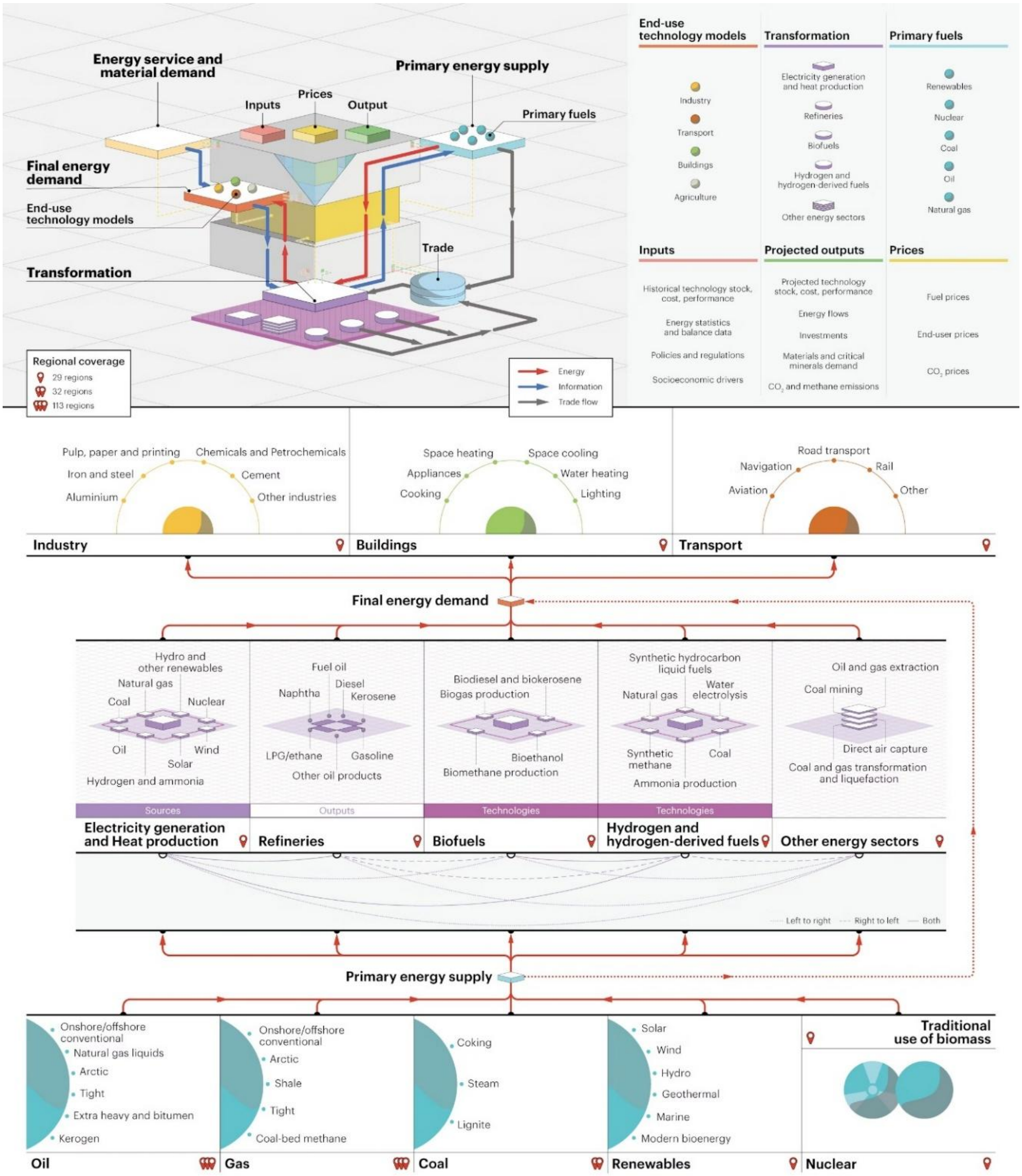

Figure 1.3: Global Energy and Climate Model Overview (IEA, 2024)

Geographical and Sectoral Resolution

The IEA's GEC Model covers 27 regions that can be aggregated to world-level results and covers all sectors across the energy system. The oil and gas supply model has 113 regions and the coal supply model 32 regions. In addition, all the 27 regions are modelled considering 4 end use-sectors, industry, buildings, transport and agriculture. For each sector and sub-sector at least seven types of energy are considered, coal, oil, gas, electricity, heat, hydrogen and renewables.

Sectoral Breakdown: Industry, Transport and Buildings

The main end-use sectors modelled are:

- The industry sector is the most energy-consuming and CO_2-emitting end-use sector. It accounts for 39% of total final energy consumption and 45% of CO2 emissions. This sector is organized into 5 energy intensive sub-sectors (Iron and steel, chemicals, non-metallic minerals, non-ferrous minerals, paper and printings) and 8 non-energy intensive sub-sectors (such as food and tobacco, machinery, mining, transportation equipment, wood and wood products).
- The transport model includes dedicated sectoral models for road transportation, aviation, maritime and rail.
- The building sector module is subdivided into residential and service sectors. Within the residential and services sectors, energy demand is subdivided into six standard end uses in buildings, namely space heating, water heating, appliances, lighting, cooking and space cooling. In addition, the demand drivers of this specific end-use sector include floor space, appliance ownership, number of households (for the residential sector) and value added (for the services sector).

Electricity Demand and Hourly Modelling

For all these sectors hour electricity demand is defined through the introduction of hourly load curve, derived from historical data. The hourly load generation is either performed at the country level or at the GEC region level. The hourly load model covers more than 75% of world electricity consumption in 2023, including, among others, China, India, the European Union, the United States and Japan.

Outputs of the Power Generation Module

The power generation module instead calculates and computes the following outcomes, while ensuring that enough electrical energy is generated to meet the annual volume of demand in each region, and that there is enough generating capacity in each region to meet the peak electrical demand:

- The amount of new generating capacity due to demand growth and for replacing retiring capacity,
- The new type of plant to be built and installed by technology,
- The amount of electricity generated by each type of plant to meet electricity demand,
- Fuel consumption of the power generation sector,
- CO_2 emissions,
- Transmission and distribution network infrastructure needed to meet new demand,
- Wholesale and end-use electricity prices,
- Investment associated with new capacity installations.

Power Sector Dispatch and Merit Order

Simulations are carried out on an annual basis, with hourly modelling for the power sector. The model is an hourly dispatch model, representing all hours in the year, setting the objective of meeting electricity demand in each hour of the day for each day at the lowest possible cost, while respecting operational constraints.

The different power plants are dispatched based on the short-run marginal operating costs (merit order) of each plant (which are mainly determined by fuel costs) to the extent required to meet demand. The dispatch, however, is defined not only by following the least-cost approach but by following constraints such as ensuring minimum generation level of different sources for the flexibility and stability of the power system, ramping constraints, etc...

Moreover, to define the dispatch, a merit order mechanism is defined and the marginal plant needed to meet demand at each point sets the wholesale electricity price.

Multi-dimensional Analysis Capabilities

The GEC Model allows to analyze different aspects of energy systems, including:

- trends in demand, supply availability and constraints, international trade and energy balances by sector and by fuel in the projection horizon,
- CO_2 emissions from fuel combustion, industrial processes and flaring; methane (CH_4) emissions from fossil fuel operations; CH_4 and nitrous oxide (N_2O) emissions from final energy demand and energy transformation, local air pollutants, and temperature outcomes,

- impact of a range of policy actions and technological developments on energy demand, supply, trade, investments and emissions,
- investment requirements in fuel and technology supply chains to satisfy projected energy demand and demand-side investment requirements,
- including trends in access to electricity and clean cooking, as well as the related additional energy demand and investments, and changes in GHG emissions,
- including the impact of the energy sector's evolution on employment in each scenario.

CO_2 Emissions and Mitigation Accounting

Regarding the outputs of the model, one of the most important is CO_2 emissions. CO_2 emissions reported from the GEC Model account for the combustion of fossil fuels and non-renewable waste, industrial process emissions, and fugitive emissions from flaring. GEC Model CO_2 emissions accounting also consider carbon capture, utilization and storage (CCUS) deployed in the electricity and heat sectors, industry and transformation sectors and carbon dioxide removal from the atmosphere through capturing CO_2 from the air (through direct air capture DAC) or from biogenic sources (Bioenergy with carbon, capture, and storage BECCS) for permanent storage in underground reservoirs.

Methodology for Emission Calculation

CO_2 emissions from fuel combustion are computed as the product of energy demand by an implied CO_2 content factor, specific for the type of fuel, sector and region, reflecting the product mix and efficiency. This value is calculated as an average of the past 3 years' value and is assumed to remain constant over the projection period.

In the model CO_2 emissions from land use and from industrial process are accounted too. In particular, the industrial sectors considered include the mineral industry (clinker, lime, limestone use, ceramics, glass), the metal industry (primary aluminum, iron and steel), chemical industry (ammonia, methanol, ethylene, soda ash), Non-energy products (lubricants and paraffin), transformation (coal-to-liquids, coal-to-gas and gas-to-liquids, hydrogen production, biofuels production).

1.4.3. Key Input and Assumptions in WEO 2024

There are several underlying macroeconomic assumptions that are used to calibrate the different scenarios of the model. The projections in WEO 2024 are obtained starting from a set of exogeneous drivers, techno-economic inputs and policies (IEA, 2024).

All the following key input and assumptions are sourced in (IEA, 2024).

GDP and population

The GEC Model 2024 GDP projections are the primary driver of energy demand. The model adopts a two-tiered approach for global GDP growth, assuming an average of 2.7% per year through 2050:

- Short-to-Medium Term (up to 2035): Projections are based on the IMF World Economic Outlook, assuming a global growth rate of 3.1% per year.
- Long-Term Horizon (2035–2050): The methodology incorporates Oxford Economics forecasts and the Solow growth model, assuming a global growth rate of 2.5% per year.

Economic assumptions remain constant across all scenarios, allowing for a direct comparative assessment of how different energy and climate choices alone, rather than fluctuations in economic growth, shape and influence the future energy landscape.

In all three scenarios the global economy is assumed to grow on average by 2.7% each year to 2050, and this growth rate varies by country, region and over time.

The GDP average annual growth rate to 2050 is assumed to be different in the different regions of the world, with the highest values reached in Africa (4%), followed by Pacif Asia (3.3%), Middle East (3.2%), Central and South America (2.4%), North America (2%) and Europe and Eurasia (1.5%).

Regarding the global population projections, IEA assumed that it expands from 8 billion people in 2023 to 9.7 billion in 2050. This assumed projection, that is the same for each scenario, is based on the median population projection of the United Nations. This increase corresponds to an annual average growth rate of around 0.7%.

The 98% of the projected increase in global population to 2050 is in emerging market and developing countries, while urban populations are increasing in all regions.

Estimates of the rural/urban split for each region are taken from UN DESA and while in 2023, about 57% of the world population is estimated to be living in urban areas, this is expected to rise to 68% by 2050.

In addition, it emerges that regions and countries covering 60% of the world population today are characterized by fertility rates below replacement levels.

Energy and CO_2 Prices

Fossil fuel international prices are scenario-dependent, while the other exogeneous drivers are assumed to be constant and unchanged in each scenario. In addition, commodity prices serve as balancing mechanisms for global supply and demand through iterative modelling.

International fossil fuel prices are both an input and an output the model and their prices represent and reflect the price levers that are needed to stimulate sufficient investment in supply to meet projected demand.

The logic behind equilibrium price formation (starting from an input trajectory) is the same as in WEM. The supply modules estimate the production of coal, natural gas, and oil under a given price trajectory, considering the costs of different supply options as well as resource availability and limits on production growth. If the assumed prices do not incentivize enough production to meet global demand, prices are adjusted upward and energy demand is recalculated accordingly. The revised demand is then fed back into the supply modules, and this iterative process continues until supply and demand are balanced for each year of the projection period. In addition, no price fluctuations are considered.

The GEC Model employs a detailed methodology to determine fuel end-use prices, starting from the international prices, which are critical in determining technology choices across different sectors and regions. The pricing structure is developed through several key steps:

- Representative Pricing: For each sector and region, a representative price is derived as a weighted average. This accounts for the specific product mix in final consumption and the price variations between countries within the same GEC region.
- Pre-tax vs. Post-tax Prices: The model starts with pre-tax prices for coal, oil, and gas, which evolve according to scenario-specific international market trends. To reach the post-tax prices used for decision-making, the framework integrates excise taxes, value-added taxes (VAT), and CO_2 prices.
- Taxation and Subsidy Assumptions: A key assumption in all scenarios is that excise taxes and VAT rates remain constant throughout the projection period. However, energy subsidies are handled dynamically: they remain constant in the Current Policies Scenario (reflecting a status quo) but are gradually phased out at varying rates in more ambitious decarbonization scenarios.
- Market Interventions: The model also incorporates governmental actions designed to shield consumers from extreme price volatility, ensuring that the simulated transition reflects realistic socio-political constraints.

Fossil fuel end price varies across the scenarios, in fact, in the STEPS the higher fossil demand led to higher prices rather than the APS and NZE scenarios.

- Regarding crude oil, the STEPS prices remain below 2023 up to 2050, following a smooth downward trend, sustained by investment and market management strategies by major producers. In the APS and NZE scenarios a more aggressive decline is assumed, reaching USD 58/barrel and USD 25/barrel respectively by 2050. In the NZE pathway, prices are increasingly dictated by the operating costs of marginal producers as demand collapses.
- Regarding natural gas, a significant expansion in Liquified Natural Gas is assumed. In STEPS the US natural gas price rises to 2030, while in Europe, Japan and China prices in 2030 are assumed to fall to level lower than those in 2023, because of policy actions in response to global energy crises. Natural gas prices gradually increase around the world after 2030. In the APS and the NZE Scenario, demand and prices are much lower around the world.
- Regarding coal, prices are assumed to decline to 2050 in all three scenarios. In the STEPS coal prices are assumed to fall by 30-50% to 2030 in importing regions, while in APS the faster decline in demand leads to a higher fall in prices. In the NZE Scenario prices decrease faster and reach very low values.

The GEC Model determines then the electricity end-use prices by aggregating wholesale prices, transmission and distribution (T&D) tariffs, system operation costs, and fiscal elements such as taxes and subsidies. The wholesale component is calculated to ensure the economic viability of the power fleet, requiring that all operating plants recover their variable costs, including fuel and CO_2 emissions cost, and that new capacity additions recover their full investment and capital costs. Beyond generation, the model incorporates regulated T&D tariffs and increasing system operation costs, which are adjusted in line with the integration of Variable Renewable Energy (VRE). To simulate this integration, the annual electricity demand is disaggregated into a four-segment load-duration curve, covering baseload, mid load, and peak load, from which the weather-dependent output of VREs is subtracted. This process defines a residual load-duration curve that must be met by dispatchable generation, ultimately determining the wholesale price based on the marginal costs of the units operating in each time segment.

Regarding carbon prices, different values are assumed according to the scenario. STEPS consider only existing and scheduled carbon pricing initiatives, and the EU ETS CO_2 is assumed to reach USD 158/ton CO_2 in 2050. In the APS, net zero emissions pledges lead to higher CO_2 prices across all regions, with prices rising by 2050 to USD 200/ton CO_2 on average in advanced economies, and to USD 160/ton CO_2 in China, India and Indonesia. In the NZE Scenario, carbon prices are introduced in all regions and cover most sectors: they rise to USD 250/ton CO_2 in 2050 in advanced economies and USD 200/ton CO_2 in major economies including China, Brazil, India and South Africa, with lower price levels elsewhere.

Policies

The assumptions about government policies are the leading difference in the outcomes of the different scenarios and are key input in the WEO. Policies are additive across the scenario, so the measures listed under the APS supplement those in the STEPS. In the definition of the model, policies like the Inflation Reduction Act (United States), Fit for 55 (European Union), Climate Change Bill (Australia), and GX Green Transformation (Japan) have been considered (IEA, 2024). In addition, the IEA's Energy Policy Inventory provides a unique database on the current state of energy policy of more than 50 countries and together with the IEA's Government Energy Spending Tracker they are used to providing input in the scenarios. In addition, in the WEO are included only the most prominent and relevant policies and measures in shaping global energy demand, while all the policies can be explored in the IEA State of Energy Policy Report published in September 2024.

Technology

In the IEA Global Energy and Climate Model, the future evolution of technology costs

learning-by-doing. These costs are linked to levels of deployment and vary by scenario.

Moreover, it is important to underline that cost reduction of technologies follow a path with highest cost reduction in the early phases of innovation and then as the technology mature cost reduction is slower. The main driver for technology cost reduction is done by policies.

In addition, the technologies included in the model are all commercially available or at least are in an advanced stage of development. Cost reductions and performance increases are considered following a learning curve approach. In addition, even if all the scenarios are characterized by the same technologies, they assume a different pace of progress as the support and degree of international co-operation on clean energy innovation increases with ambition on decarbonization.

Several databases are used to define the clean innovative technologies available and track their status, such as the Clean Technology Guide, the Clean Energy Demonstration Projects Database, the Tracking Clean Energy Progress, the Hydrogen Production Project Database and the Global EV Outlook.

In addition, the technology/power plant considered for the power generation sector includes:

- Coal, oil and gas steam boilers with and without CCUS,
- Combined-cycle gas turbine (CCGT) with and without CCUS,
- Open-cycle gas turbine (OCGT),
- Integrated gasification combined cycle (IGCC),
- Fuel cells,
- Bioenergy with and without CCUS,
- Geothermal,
- Wind onshore and offshore,
- Hydropower (conventional),
- Solar photovoltaics,
- Concentrating solar power,
- Marine,
- Nuclear,
- Utility-scale battery storage (4h).

1.5. Methodology of the Comparative Analysis

1.5.1. Rationale for Selecting WEO 2010 and WEO 2024 Editions

The choice to focus on the 2010 and 2024 editions of the World Energy Outlook is based on different methodological reasons, ensuring a robust comparison between past projections and the current state of the art.

Selection of WEO 2010: The Ex-Post Benchmark

The WEO 2010 (IEA, 2010) was selected as the historical baseline for the comparative analysis for the following reasons:

- Optimal Evaluation Horizon: Published with a 2035 horizon, it provides a sufficient timeframe for a meaningful ex-post evaluation. It allows for a direct comparison of projections for the years 2015, 2020, and 2025 against the actual data observed between 2010 and 2024. Moreover, it formally introduced the New Policies Scenario alongside the Current Policies and 450 Scenarios.

- Minimizing Immediate Shock Bias: Unlike adjacent editions, WEO 2010 is relatively "clean" from the noise of immediate crises. The WEO 2009 was heavily influenced by the 2008 financial crisis, making its short-term trends unrepresentative of long-term trajectories. Conversely, the 2011 and 2012 editions already incorporated the post-Fukushima policy shifts (nuclear phase-outs). By contrast, WEO 2010 was published just months before the Fukushima disaster.

Selection of WEO 2024: The current state of the art

The WEO 2024 (IEA, 2024) was selected as the contemporary reference for the following reasons:

- The Contemporary Benchmark: As the latest comprehensive edition, it synthesizes the most recent trends in supply and demand, discussing their implications for energy security, emissions, and economic development. It serves as the definitive benchmark for aligning current definitions and contexts.
- Standardized Scenario Framework: WEO 2024 utilizes the current "standardized triad" of scenarios: the Stated Policies Scenario (STEPS), the Announced Pledges Scenario (APS), and the Net Zero Emissions by 2050 (NZE) Scenario. This framework is essential for understanding the current gap between policy intentions and climate goals.
- Advanced Modelling Framework (GEC Model): The 2024 edition is powered by the Global Energy & Climate (GEC) Model, which integrates the previous WEM and ETP models. This sophisticated framework covers 27 regions across all sectors with hourly power sector modelling. It also includes explicit modules for advanced technologies, investment flows, methane emissions, and climate variables (via the MAGICC model), ensuring highly robust comparisons across different geographies and technologies.

1.5.2. Temporal Scope and the 1990 Baseline

The historical data series starts from 1990 to assure a rigorous empirical validation and comparison of the energy projections. This specific starting point was selected based on three fundamental criteria:

- Institutional Baseline: 1990 serves as the primary international reference year for greenhouse gas emissions, notably as the base year for the Kyoto Protocol. Aligning the analysis with this baseline ensures consistency with global climate policy literature.

- Energy Regime Shifts: The period from 1990 to the present encompasses a complete cycle of structural transformations, including post-Soviet economic restructuring, the hyper-industrialization of emerging Asian economies, and recent technological disruptions such as the collapse of renewable energy costs and the US shale revolution.
- Identification of Exogenous Shocks: The 1990–2024 window includes well-defined, critical events that have significantly affected primary energy demand, the power mix, and emission trajectories, serving as a stress test for the predictive capacity of the WEO models.

The 1990-2024 timeframe accounts for the following events:

- 1990–1991 Gulf War (L Archer, 1990): Oil supply disruptions and increased price volatility.
- 1997–1998 Asian Financial Crisis (Mabro, 2009): Regional economic recession leading to a collapse in crude oil prices.
- 1997 (Enforced 2005) Kyoto Protocol (UNFCCC, s.d.): The first international legal constraint on emissions, influencing investment expectations.
- Summer 2003 European Heatwave (A. De Bono, 2004): Peaks in cooling demand and operational constraints for nuclear and hydroelectric plants due to thermal limits and low water levels.
- 2008–2009 The Great Recession (Sadorsky, 2020): A significant contraction in global energy demand and CO_2 emissions.
- From 2008/09 US Shale Revolution (Financial Times, 2015): Rapid expansion of shale gas and tight oil, impacting global fuel competitiveness and power sector dynamics.
- March 2011 Fukushima Disaster (Masatsugu Hayashi, 2013): Sudden suspension of nuclear power in Japan and subsequent global policy reconsiderations, leading to increased fossil fuel reliance.
- 2014–2016 Oil Price Collapse (Prest, 2018): Driven by OPEC's production strategy and rising non-OPEC supply, resulting in a sharp decline in upstream investments.
- Dec 2015 Paris Agreement (UNFCCC, s.d.): A turning point in global climate expectations, influencing long-term energy scenarios and capital allocation.
- 2020 COVID-19 Pandemic (Liu, 2022): A historic collapse in global mobility and primary demand, with CO_2 emissions falling by 6.5%.

- 2021–2022 Global Gas Crunch (IEA, 2021): Supply-demand imbalances during the post-pandemic recovery leading to record-high energy prices.
- Feb 2022 Onward Russian Invasion of Ukraine (IEA, 2022): Drastic cuts in Russian gas exports to the EU, a global energy price crisis, and a total reconfiguration of energy trade flows.
- 2022–2024 Recurrent Extreme Weather (EMBER , 2025): Sharp spikes in cooling requirements during 2024 heatwaves heavily strained the three largest global power markets. The subsequent reliance on fossil fuel generation to meet these peaks highlights the persistent vulnerability of current grids and the urgency of deploying more resilient, clean energy solutions.

1.5.3. Historical Data Retrieval

A rigorous data collection process was implemented to ensure the integrity and comparability of the historical series. To maintain maximum source consistency, historical data for the 1990–2024 period were retrieved by systematically analyzing past editions of the IEA World Energy Outlook. Each specific year's data point is extracted from the WEO edition that utilized it as the "Base Year" for model calibration. Typically, this corresponds to one or two years prior to the report's publication date. By extracting these specific anchor points, the study ensures that the historical baseline reflects the exact figures upon which the IEA based its subsequent projections. Table 1.1 details the WEO edition (second column) from which the historical data for each specific year (first column) were sourced.

Table 1.1: Historical Data Retrieval

Year	WEO Edition
1990	2007
1995	1998
2000	2002
2005	2007
2010	2012
2011	2013
2012	2014
2013	2015
2014	2016
2015	2017
2016	2018
2017	2019
2018	2020
2019	2021
2020	2022
2021	2023
2022	2024
2023	2024
2024	2024

1.5.4. Selection of Key Variables and Methodological Adjustments

The analysis focuses on three specific variables, that are selected as both output of the WEOs and essential pillars of the energy transition. These variables allow to describe and give a complete picture of the global energy landscape:

- Total Primary Energy Demand*:* this variable represents the total amount of energy a system consumes before it is converted into end-use products such as electricity. The main drivers are population growth, GDP development and energy efficiency.
- Total Electricity Production*:* this variable focuses on the mix of sources used to generate electricity. The main drivers are the Technology costs (LCOE), grid infrastructure and energy storage capacity.
- Total CO_2 Emissions*:* this variable represents the final environmental impact of energy activities and is the environmental results of the interactions between the first two. The main drivers are the carbon intensity of the energy mix and the total volume of fuel burned.

These variables are chosen because they are consistently available across all World Energy Outlook editions and are directly linked to key market drivers and policy levers, such as energy efficiency, renewable energy penetration, fossil fuel price dynamics, and carbon pricing. The relationship between these three points allow to describe the Energy Transition, in fact to achieve Net Zero is necessary to simultaneously reduce or stabilize the demand, decarbonize the mix and minimize the resulting emissions.

Structural and Methodological Evolution of WEO Outputs

An important challenge that arises in this comparative analysis is linked to the collection of data from the annexes of different WEOs editions. In fact, over the editions the IEA has significantly revised and updated its reporting framework, leading to several discrepancies, affecting different areas, including the nomenclature and unit of measurement of variables, the computational methodology for CO_2 emissions, the technology and source granularity, the geographical boundaries and regional aggregation and finally the scenario definitions and frameworks.

To ensure a reliable comparison over the entire timeframe of the analysis, the following methodological alignments were performed:

- CO_2 Emissions Recalibration: It is important to note that the IEA's methodology for calculating CO_2 emissions has evolved over time. To maintain consistency, historical values from earlier WEO editions have been reconverted and updated to align with the more recent methodology used in the WEO 2024 (IEA, 2024) . This prevents accounting discrepancies from being misinterpreted as actual historical trends.

- Primary Energy Nomenclature (TPED vs. TPES): In earlier editions, primary energy was defined as “Total Primary Energy Demand” (TPED), whereas recent reports utilize the term “Total Primary Energy Supply” (TPES). While the terminology has shifted, the underlying definition remains substantially unchanged for the purposes of this global analysis.
- Electricity Generation: The definition of “Total Electricity Production” has remained stable throughout the timeframe considered, allowing for a direct and transparent comparison across different reports.

1.5.5. Methodological Alignment of CO_2 Emissions Data

Following a data retrieval process used for gathering data from the old editions of WEOs, a critical harmonization step was performed to align all historical CO_2 emissions values with the most recent and updated methodology utilized in the WEO 2024 edition. Throughout the various editions of the World Energy Outlook, the IEA has refined its computational methods for emissions (e.g., changes in emission factors or the inclusion of specific sub-sectors). Specifically, after collecting the CO_2 emission values for all years (1990-2024) from various WEO editions as detailed in Table 1.1, the methodology used in each edition, from which the historical data were sourced, was analysed. This led to the definition of seven clusters, as shown in Table 1.2. These clusters aggregate WEO editions in which the CO_2 emission accounting methodology remained uniform. Subsequently, correction factors were computed to convert emission data from older editions into values aligned with the WEO 2024 methodology, ensuring consistency across the entire dataset. For computing these correction factors this study applied the “Time Series Consistency” techniques established by the Intergovernmental Panel on Climate Change (William Irving, 2006).

Specifically, two distinct techniques were employed. The first, the 'Overlap Approach', consists in calculating the correction factor as the ratio between values from two different series for a shared common year. This method is utilized when the two series, namely the emission trajectory of an older WEO edition and that of the WEO 2024, have at least one year in common. The second technique, the 'Composite Correction Factor', is used when a series must be adjusted relative to the reference series, but no common years are available for direct comparison. In such cases, an intermediate correction factor is defined to align the first series with an intermediate one that shares a common year. The first series is then corrected relative to the reference by multiplying this intermediate factor by the intermediate series' own correction factor relative to the reference.

The Overlap Approach

The primary technique employed for this harmonization is the 'Overlap Approach' (William Irving, 2006). This method involves calculating a corrective factor based on the ratio between emission values for years common to both the historical edition and the WEO 2024 reference series. For a given overlapping year t, the corrective factor (k) is determined as follows:

$$k = \frac{E_{\text{WEO 2024},t}}{E_{\text{WEO old},t}} \quad (1.1)$$

Where E represents the CO_2 emission value. This factor is then applied to the entire series of the older edition to bring it into alignment with the 2024 standards.

Composite Correction Factors

In cases where a direct overlap between a specific historical edition and the WEO 2024 was unavailable, a composite (or chained) correction method was utilized (William Irving, 2006). This involved identifying an intermediate WEO edition that shared common data points with both the older report and the 2024 version. A 'chained' factor was then calculated by multiplying the successive corrective factors:

$$k_{\text{final}} = k_{\text{old}\rightarrow\text{intermediate}} \times k_{\text{intermediate}\rightarrow\text{WEO 2024}} \quad (1.2)$$

This factor is then applied to the entire series of the older edition to bring it into alignment with the 2024 standards.

Methodological Clusters and Variable Consistency

Based on the evolution of CO_2 definitions, the various WEO editions are categorized into seven distinct methodological clusters as in Table 1.2. Each cluster represents a period during which the IEA maintained a stable internal methodology for emission computation.

It is important to underline that each CO_2 Emission Definition is taken from the Annex of each WEO Edition.

Table 1.2: Methodological Cluster

Cluster	WEO Editions	CO_2 Emission Definition	K factor
1°	1998	Total CO_2 includes carbon dioxide emissions: from the combustion of fossil fuels and non-renewable wastes, from industrial and fuel transformation processes (process emissions); and CO_2 emissions from flaring and CO_2 removal.	1.07
2°	2002, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014	CO_2 emissions do not include emissions from industrial waste, non-renewable municipal waste and flaring. (1996 guidelines)	1.09
3°	2015, 2016, 201, 2018	CO_2 emissions do not include emissions from industrial waste, non-renewable municipal waste and flaring. (2006 guidelines)	1.11
4°	2019	Total CO_2 includes carbon dioxide emissions from "other energy sector" in addition to the power and final consumption sectors shown in the tables. Total and power sector CO_2 emissions also account for captured emissions from bioenergy with carbon capture, utilisation and storage (CCUS). CO_2 emissions do not include emissions from industrial waste and non-renewable municipal waste.	1.08
5°	2020	Total and power sector CO_2 emissions also account for captured emissions from bioenergy with carbon capture, utilisation and storage (BECCS). CO_2 emissions do not include emissions from industrial waste and non-renewable municipal waste. Process CO_2 emissions from industrial production and fuel transformation are included only at the world level.	1.08
6°	2021	Total CO_2 includes carbon dioxide emissions from the combustion of fossil fuels and non-renewable wastes, from industrial and fuel transformation processes (process emissions) as well as CO_2 removals.	1.01
7°	2022, 2023, 2024	Total CO_2 includes carbon dioxide emissions: from the combustion of fossil fuels and non-renewable wastes, from industrial and fuel transformation processes (process emissions); and CO_2 emissions from flaring and CO_2 removal.	1.0

The emission data for a specific year, extracted from a WEO edition belonging to a certain cluster, is multiplied by a correction factor to align it with the WEO 2024 methodology, ensuring full comparability across the dataset.

For clusters 2°, 4°, 5°, 6°, and 7°, the correction factor is identified using the Overlap Approach, as the year 2010 is available as a common reference point with WEO

2024. Conversely, for clusters 1° and 3°, it is necessary to define a composite correction factor, given the absence of a year allowing for a direct comparison with the historical data reported in the WEO 2024 edition.

Furthermore, an intermediate K factor is calculated for clusters 1° and 3° relative to cluster 2°, as both datasets shared common data for the year 1990. This intermediate $K_{Intermediate}$ is then multiplied by the correction factor of cluster 2° to determine the final correction factor relative to WEO 2024 for clusters 1° and 3° as well.

$$K_{Cluster\ 1,3} = K_{Intermediate\ (1,3 \to 2)} * K_{Cluster\ 2} \quad (1.3)$$

Finally, a consistency check is performed for the other two primary variables: Total Primary Energy Demand (Supply) and Total Electricity Production. The analysis confirmed that their definitions and accounting boundaries have remained fundamentally coherent and consistent across all analyzed editions. Consequently, these variables did not require the application of corrective factors, allowing for a direct comparison of the raw data.

1.5.6. Formal Definitions of Analysed Variables

Consistent with the previous discussion, the analysis focuses on three main variables: Total Primary Energy Demand, Total CO_2 Emissions, and Total Electricity Generation.

The variables are defined according to the current 2024 IEA methodological standards as reported in the WEO 2024 (IEA, 2024).

- The nomenclature 'Total Primary Energy Demand' (TPED) has been updated to 'Total Energy Supply' in the WEO 2024. However, this represents a purely terminological shift, as both the definition and the categories of energy considered remain consistent. TES is calculated as the sum of electricity and heat generation, the "other energy sector" (excluding electricity, heat, and hydrogen), and the total final consumption (excluding electricity, heat, and hydrogen). It is important to note that TES specifically excludes ambient heat captured by heat pumps and electricity trade between regions. Values are expressed in Million tonnes of oil equivalent (Mtoe) to maintain comparability with the 2010 baseline.
- The definition of CO_2 emissions adopted account for both positive emissions and removal technologies, leading to a shift toward a net-accounting framework. Total CO_2 emissions include CO_2 from the combustion of fossil fuels and non-renewable wastes, as well as process emissions from industrial and fuel transformation activities, flaring, and domestic/international aviation and shipping. It includes CO_2 captured and removed that consider CO_2 recovered via CCUS facilities, DAC, BECCS, while excluding CO_2 used

for urea production. The unit of measurement is million tonnes of carbon dioxide.

- Total Electricity Generation is the one generated across all the technology types and is a gross generation since include the ‘own use’ of electricity by the generator, so the energy consumed by the power plant itself during operation. The unit of measurement is Terawatt-hours (TWh).

1.6. Comparative Results and Historical Validation

In the following section several graphs are reported. They are representing the evolution of the Total Primary Energy Demand (Mtoe), Total Electricity Production (TWh) and Total CO_2 Emissions (Mt) for the World. Energy demand and electricity production are also reported for separate specific sources, highlighting the evolution of fossils and renewables technologies. The specific sources considered in the analysis include Coal, Oil, Natural Gas, Nuclear, Solar Pv, Wind, Biomass, Geothermal and Hydro.

In the charts the red curve represents the WEO 2010 projections, the blue one the WEO 2024 projections, the light blue the historical trend. In addition, the light red curve represents the linear extrapolation of WEO 2010 projections up to 2050.

Instead, the circle, the square and the triangle indicators represent respectively the conservative, the intermediate and the ultimate scenarios in each WEOs.

The chart descriptions have been enriched with insights from specific chapters of the WEO 2024 and WEO 2010 editions, corresponding to their respective trajectories. Citations for these sections are provided once at the conclusion of each section.

1.6.1. Energy Demand

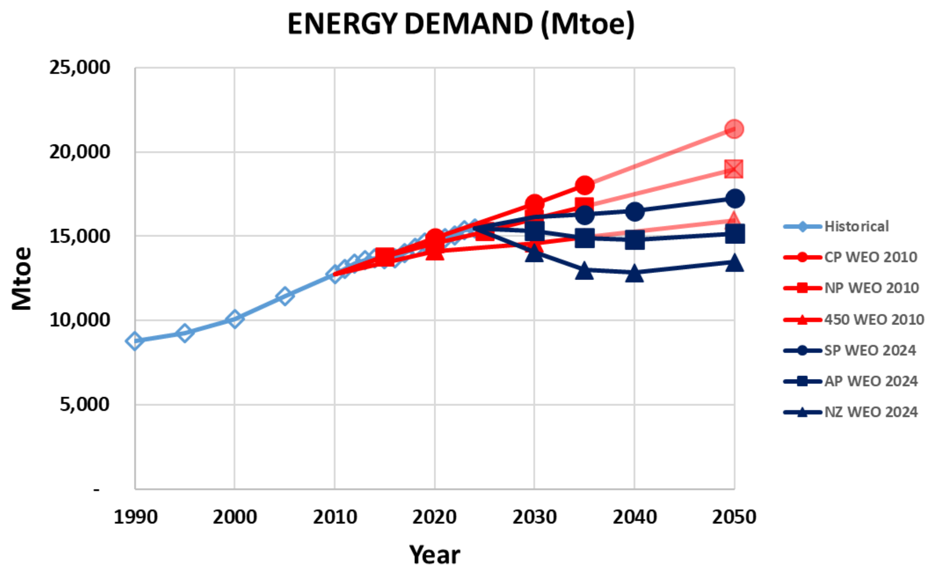

Figure 1.4: Energy Demand

Figure 1.4 illustrates the comparative analysis of the historical trend of Total Primary Energy Demand (from 1990 to 2024) against projections from the IEA's World Energy Outlook (WEO) 2010 and WEO 2024. Historically, energy demand has grown linearly at a nearly constant rate, correlating strongly with global population growth and economic expansion; notably, this historical trajectory closely tracked the WEO 2010 Current Policies projection until recent years.

The analysis of the 2010 projections (red curves) highlights a paradigm where economic development was assumed to drive an inevitable increase in energy demand across all scenarios. In the New Policies Scenario (2010), which accounted for existing policies and declared intentions, global demand was projected to rise by 1.2% annually between 2008 and 2035, reaching 16,750 Mtoe (an increase of 36%). This growth was even more pronounced in the Current Policies Scenario, averaging 1.4% per year. Even in the ambitious 450 Scenario, designed to limit global warming to 2°C, demand was still expected to grow by roughly 22% (0.7% per year), reflecting the varying intensity of policy actions aimed at climate change and energy security (IEA, 2010).

Instead, the WEO 2024 projections (dark blue curves) are characterized by a decline in the projections compared to the outcomes of the previous edition. Except for the Stated Policies Scenario (STEPS), which shows a plateau, all other scenarios project a net reduction in total primary energy demand. This slowdown and subsequent decline are driven by the synergy of three fundamental factors, including technological progress, efficiency improvements and changes in the structure of the global economy.

First, technical efficiency has accelerated. Improvements in processes and equipment are now heavily reinforced by stringent regulations, such as minimum energy performance standards. While present in all scenarios, the pace of these efficiency gains is significantly more aggressive in the Announced Pledges Scenario (APS) and the Net Zero Emissions (NZE) scenario compared to STEPS.

Second, the global economic structure is shifting away from energy-intensive heavy industry towards the service sector and digitalization, which generate value with lower energy inputs. This evolution marks a shift from past trends; growth rates for energy-intensive materials like steel and aluminum are projected to moderate, a shift largely influenced by the structural transformation of China’s economy.

Finally, and perhaps most critically, is the impact of electrification and renewables. This factor is increasingly influential because renewable technologies are inherently more efficient than fossil fuel combustion, which suffers from significant thermodynamic conversion losses (waste heat). Unlike fossil fuels, most renewables (wind, solar, hydro) are considered 100% efficient in primary energy accounting, as they do not require extraction or combustion. Consequently, the shift towards electrification drastically reduces the total primary energy required. This is because electric technologies (such as electric vehicles) are thermodynamically far more efficient than fossil-fuel equivalents, which lose most of their input energy as waste heat during combustion. As a result, the global economy can deliver the same level of services using significantly less raw energy input, effectively reducing the total energy demand (IEA, 2024).

1.6.2. Electricity Production

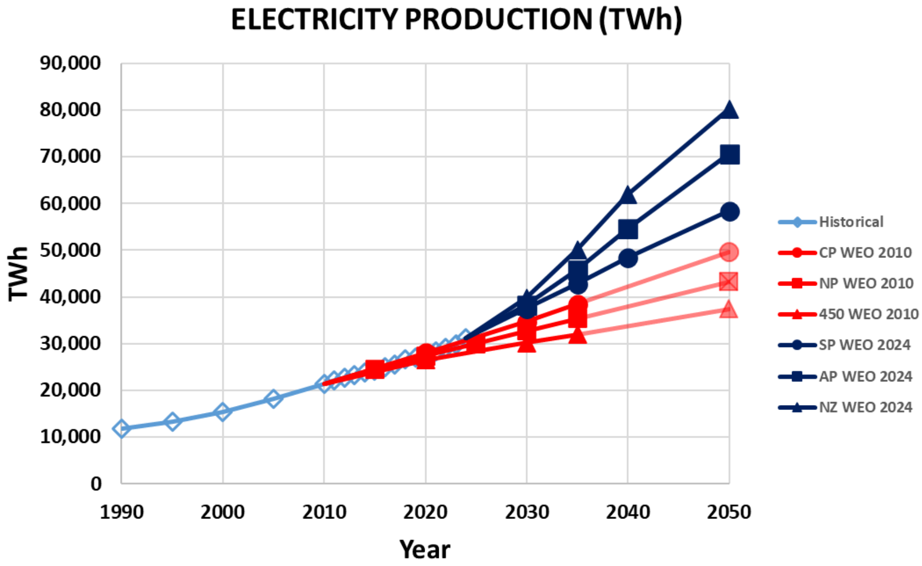

Figure 1.5: Electricity Production

Figure 1.5 illustrates the historical trend and the IEA World Energy Outlooks (WEO) projections for Total Electricity Production from 1990 to 2050. A crucial observation, and a defining feature of this comparison, is the systematic inversion of the projection logic compared to the Total Primary Energy Demand chart (Figure 1.4). While Figure 1.4 showed 2024 projections falling below those of 2010, in this case, the 2024 projections (blue lines) are systematically higher than the 2010 outlooks (red lines).

In 2010, the prevailing idea assumed that energy efficiency would constrain the growth of electricity demand alongside total energy demand. Consequently, the most climate-ambitious path, the 450 Scenario (red triangles), projected the lowest electricity output, reaching only approximately 37,000 TWh by 2050. The idea was that climate mitigation required an overall reduction in consumption, including electricity. While all 2010 scenarios projected growth following the 2008 financial crisis, the rates were conservative: the Current Policies Scenario anticipated a 2.5% annual increase between 2008 and 2035, while the New Policies and 450 Scenarios consider even lower growth (2.2% and 1.9% per year, respectively) due to policies aimed at curtailing emissions through efficiency (IEA, 2010).

Conversely, the 2024 outlook represents a fundamental reversal of this logic. Decarbonization is now understood to rely on a massive structural shift from fossil fuels to renewable electricity. As a result, the "greenest" scenario, the Net Zero Emissions (NZE, blue triangles), now projects the highest absolute electricity production, reaching approximately 80,000 TWh by 2050. This creates a huge divergence between results: the modern Net Zero scenario envisages more than double the electricity generation of the 2010 "450 Scenario." The contemporary message is clear: saving the climate requires producing vast quantities of clean electricity to power sectors that previously relied on direct fossil fuel combustion.

The 2024 projections are driven by rapid electrification in sectors that were not previously anticipated to be such massive consumers:

- Mobility: The widespread adoption of Electric Vehicles (EVs) replacing internal combustion engines.
- Heating: The transition from gas boilers to electric heat pumps in residential and commercial buildings.
- Industry: The electrification of thermal processes and the production of green hydrogen via electrolysis, which is highly electricity intensive.
- Digitalization: The rising energy needs of data centers and Artificial Intelligence infrastructure.

Finally, the historical trajectory (light blue line) validates this modern perspective. Electricity production has grown consistently, often exceeding the levels predicted in 2010. Notably, the recent trendline (2023-2024) points sharply upward, showing a much stronger alignment with the steep growth slopes of the WEO 2024 scenarios than with the more moderate growth predicted in the past.

1.6.3. Total CO_2 Emissions

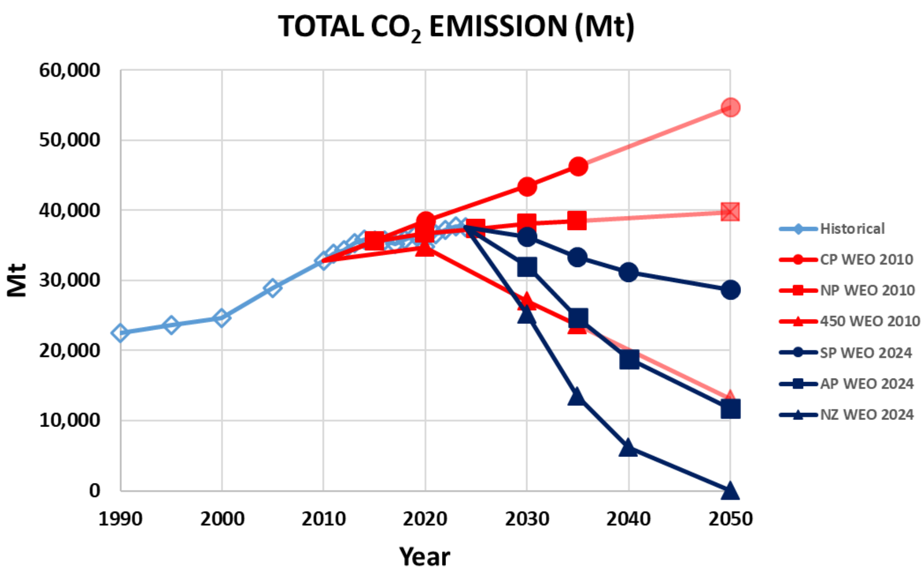

Figure 1.6: Total CO_2 Emission

Figure 1.6 represents the historical trend and the WEO 2010 and 2024 projections of total CO_2 emissions. The historical line is characterized by a constant growth in emissions from 1990, interrupted by a sharp, temporary decline in 2020 caused by the COVID-19 pandemic, after which the curve begins to flatten into a plateau, although energy-related CO_2 emissions increased by just over 1% in 2023 to reach a record high of 37.7 gigatons (Gt). Looking back at the 2010 perspective, the CP WEO 2010 (Current Policies) scenario depicted a catastrophic "business-as-usual" trajectory where emissions reached 47 Gt by 2035, while the NP WEO 2010 (New Policies) anticipated a stabilization around 38 Gt, while the 450 WEO 2010 scenario offered an optimistic path to maintain CO_2 at 450 ppm through drastic reductions. This 450-emission trajectory was determined in two stages: first, a path to 2020 based on the Copenhagen negotiations, and second, a post-2020 path requiring an early peak and rapid decline to stabilize atmospheric concentrations. Even with ambitious interpretations of the Copenhagen Accord, the 450 Scenario requires a 49% reduction compared to the Current Policies scenario, achieved through a near-doubling of annual efficiency improvements and the near-universal removal of fossil fuel consumption subsidies. Key actions in China, the US, the EU, Japan, and India are expected to account for half of these reductions, with China alone contributing 35% of the abatement in 2035 and fossil-fuel subsidy phase-outs serving as a crucial pillar in the Middle East (IEA, 2010).

Turning to the 2024 projections, the situation has changed radically thanks to technological evolution in renewables and electric vehicles and new climate policies. The SP WEO 2024 (Stated Policies), based on policies currently in force, consider a decline trend where emissions peak just over 33 Gt in 2035 and fall to less than 29 Gton in 2050, demonstrating that current policies have bent the curve downward; here, advanced economies drive around 60% of the decline, while emerging market reductions are partially offset by increases in road transport and industry. The AP WEO 2024 (Announced Pledges) assumes that all government promises are met, lowering emissions to around 32 Gt in 2030 and 12 Gt in 2050, with advanced economies approaching zero and emerging economies emitting around 10 Gt. Finally, the NZ WEO 2024 (Net Zero) represents the ideal scenario to limit warming to 1.5°C, where global emissions fall by 33% to around 25 Gt in 2030 and reach net zero in 2050; in this pathway, advanced economies achieve aggregate net zero in the electricity sector by 2035 and the wider economy by the mid-2040s, utilizing technology to remove around 0.9 Gt of CO_2 in 2050, while China reaches net zero around 2050 (IEA, 2024).

The emission gap between the Stated Policies and the Net Zero scenario remains immense, requiring the reduction of more than 500 cumulative gigatons of CO_2 over the next 25 years.

These pathways lead to different temperature outcomes: STEPS results in a global temperature rise of roughly 2.4°C in 2100 (with a one-third chance of exceeding 2.6°C), APS limits the rise to around 1.7°C, and the NZE Scenario sees a peak of less than 1.6°C around 2040 before falling back to below 1.5°C by 2100 (IEA, 2024).

1.6.4. Total CO_2 Captured

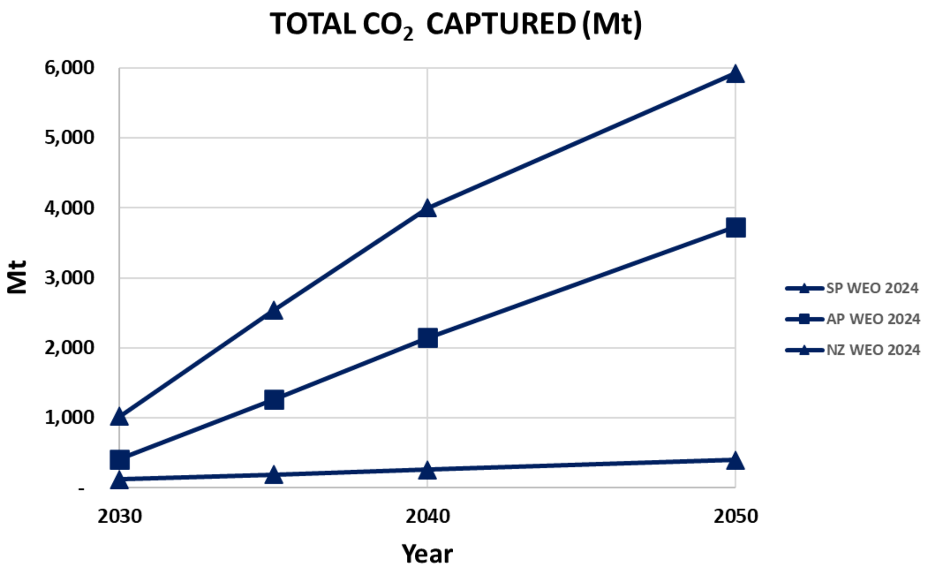

Figure 1.7: Total CO_2 Captured

Figure 1.7 represents the WEO 2024 projections for (all sector) captured CO_2 across three different scenarios, and there is only the WEO 2024 representation since no data for the WEO 2010 were available in the annexes. The main dominant feature is the enormous distance between the bottom line of the Stated Policies and the top line of the Net Zero. The STEPS line reflects the current reality where, without strong incentives, Carbon Capture, Utilization and Storage (CCUS) remains very low due to high costs. In this scenario it is projected to capture less than 500 Mt (megatons) annually even by 2050. While the NZE line illustrates the trajectory necessary to limit the temperature increase of 1.5°C by 2050, requiring a massive increase up to 6,000 Mt (6 Gt) captured annually by 2050. Currently, CCUS is applied at around 45 facilities worldwide with a capture capacity of roughly 50 Mt CO_2 per year. While the expansion of operational capacity has been slow, announced projects indicate potential strong growth: if all projects announced worldwide were realized by 2030, they would reach 435 Mt of capture capacity and around 615 Mt of storage capacity per year. However, up to now only 20% of the announced capture capacity and 15% of the storage capacity have reached a final investment decision or are already in operation.

Current project announcements for the coming decade are insufficient. They fail to reach the 1.3 Gt CO_2 capture target required by 2035 for the Announced Pledges Scenario (APS) and lag significantly behind the 2.5 Gt needed for the Net Zero (NZE) scenario. To get closer to NDC and net zero targets, new projects are urgently needed to reduce emissions from fossil fuel-fired power plants and hard-to-abate industrial processes. In both the APS and NZE scenarios, CCUS is also employed to produce low-emissions hydrogen from natural gas, accounting for 10-15% of total emissions captured annually by 2050.

In the power sector specifically, capture technologies offer the ability to significantly reduce emissions from coal-fired plants, which emitted 11.3 Gt CO_2 in 2023 (almost 30% of global energy-related emissions). With around 9,000 coal-fired units in operation today, CCUS could play a vital role in keeping climate targets within reach. This deployment supports emission reductions for coal plants alongside other strategies such as repurposing them for flexibility or retrofitting them to use low-emissions ammonia (IEA, 2024).

1.6.5. Coal Energy Demand and Coal Electricity Production

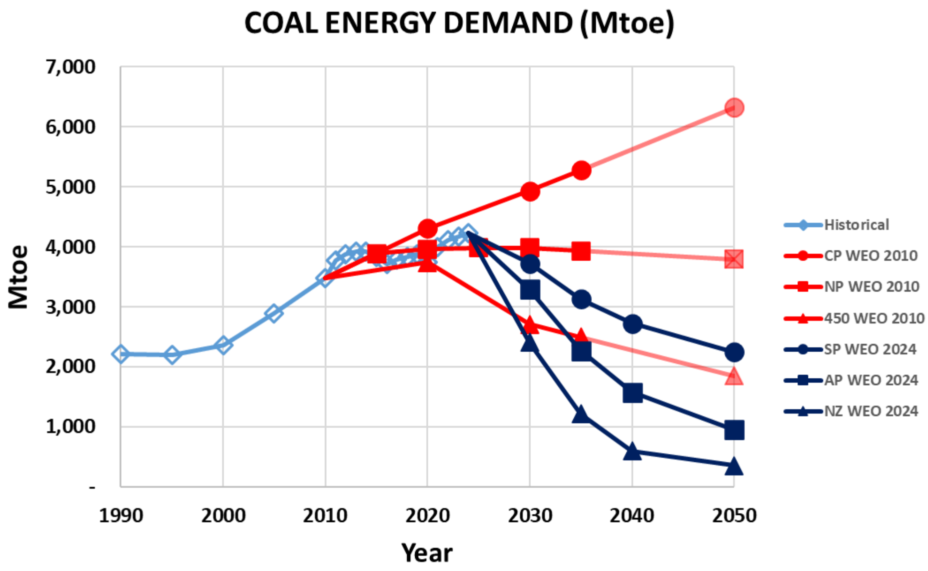

Figure 1.8: Coal Energy Demand

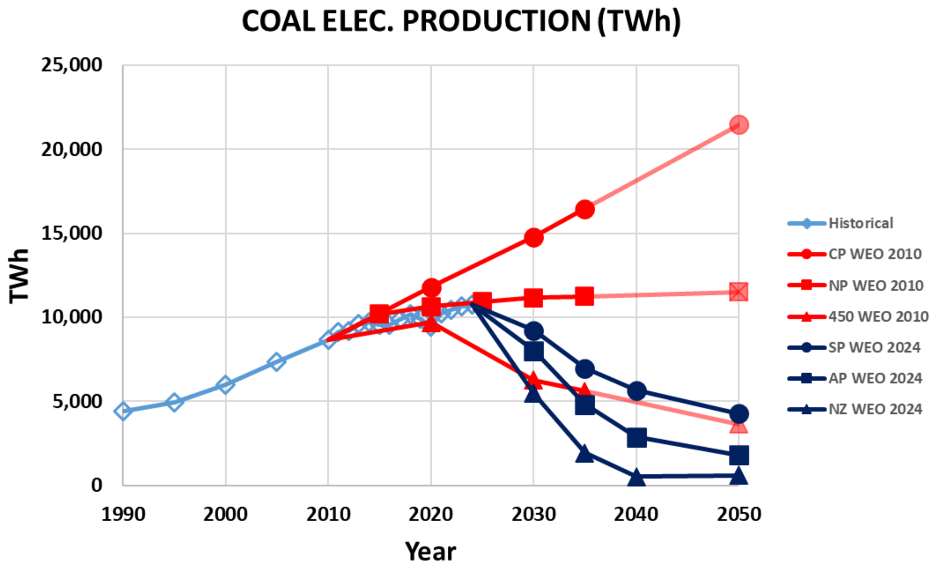

Figure 1.9: Coal Electricity Production

Figure 1.8 and Figure 1.9 represent the historical trend and the WEO 2010 and 2024 projections of energy demand and electricity production for coal respectively. Historically, both graphs show consistent growth from 1990 until approximately 2015, but around 2015-2016, a slowdown is observed in coal energy demand; while historical electricity production (Figure 1.8 , light blue line) continued to grow slightly to stabilize on a recent plateau of approximately 10,000 TWh. Instead, by 2021 primary energy demand for coal (Figure 1.8) flattened around 4,000 Mtoe.

The Current Policies scenario of the WEO 2010 erroneously predicted a very strong and total dependence on coal, expecting electricity production to double and exceed 16,000 TWh by 2035, but electricity production from coal has been lower due to the collapsing costs of renewables and the shift to gas. Consequently, the historical trend aligned much more closely with the New Policies Scenario.

Regarding the 450 scenario, it can be stated that both coal demand and electricity production were determined in two stages: first, a path to 2020 based on the Copenhagen negotiations, and second, a post-2020 path requiring an early peak and rapid decline to stabilize atmospheric concentrations.

In that 2010 New Policies context, coal demand was expected to increase by around 20% between 2008 and 2035, driven entirely by non-OECD countries whose share of total demand was projected to rise from 66% to 82%, with China, India, and Indonesia accounting for nearly 90% of incremental growth.

Specifically, China was projected to remain the largest consumer and was projected to install around 600 GW of coal new capacity by 2035, comparable to the current combined capacity of the US, EU, and Japan. India was set to become the second-largest consumer around 2030, and Indonesia to take the fourth position behind the United States by 2035. (IEA, 2010).

Moving to WEO 2024, projections now start from the awareness that the coal peak has been reached or is imminent. Analyzing the Stated Policies (STEPS) scenario, it can be stated that even without new laws, coal is destined to fall, with electricity production dropping to roughly 4,280 TWh in 2050.

Demand drops by around 25% by 2035 from 2023 levels, driven by rapid reductions in advanced economies, where 88% of the 26 GW retired in 2023 were located, while emerging economies continue to add capacity, such as the 47 GW added by China in 2023.

However, the gap with the Net Zero (NZE) scenario is extreme: to reach climate goals (the dark blue triangles), coal use must collapse vertically starting today, falling by around 70% by 2035 and over 90% by 2050, with electricity generation reaching zero earlier than total demand because it is easier to replace coal in power plants than in heavy industry.

In the NZE scenario, the industrial sector overtakes power as the largest coal user by 2035, and over 75% of remaining emissions are captured via CCUS.

Currently, while fossil fuels provided 60% of global electricity in 2023, with coal at 36% (its lowest share in 50 years), the transition is underway; Austria, Belgium, Portugal, and Sweden have already phased out coal-fired power, the UK closed its last plant in September 2024, and Slovakia aims to do so by the end of 2024 (IEA, 2024).

1.6.6. Oil Energy Demand and Oil Electricity Production

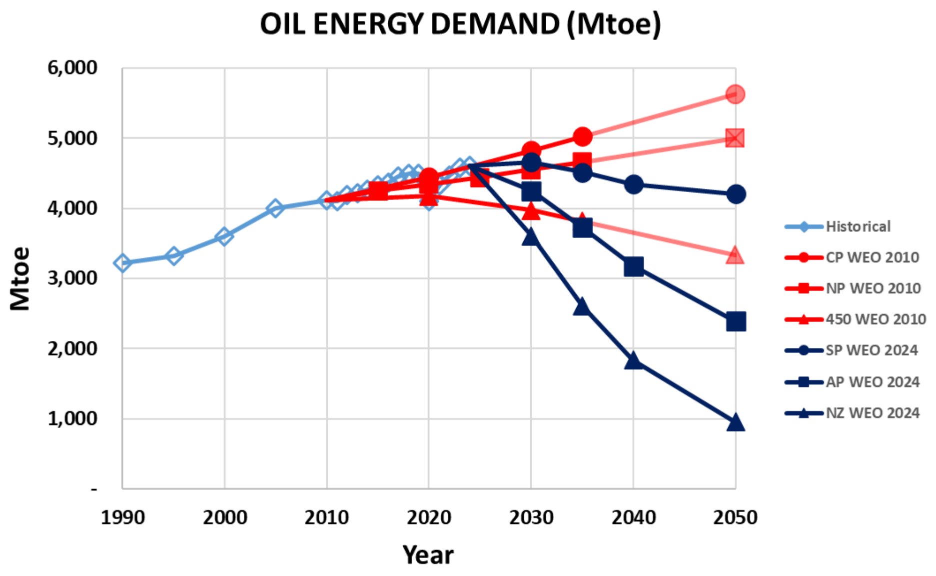

Figure 1.10: Oil Energy Demand

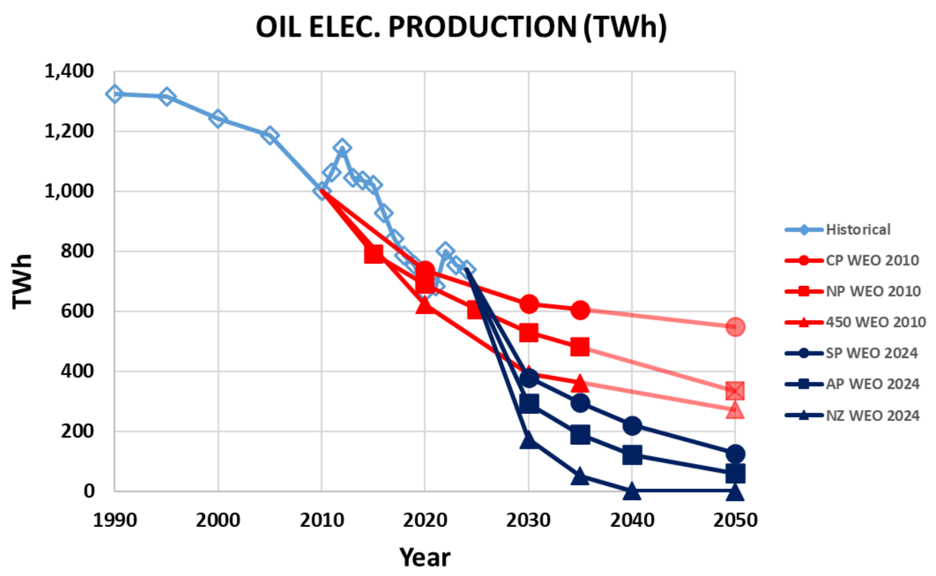

Figure 1.11: Oil Electricity Production

Figure 1.10 and Figure 1.11 representing oil energy demand and electricity production from oil showed the historical rise of oil in transport with its structural decline in the power sector. Historically, the two variable have moved in opposite directions: while primary oil demand (Figure 1.10) grew steadily from 1990 to 2019, driven by the transport and petrochemical sectors, electricity production from oil (Figure 1.11) has been in a long-term structural decline, falling from over 1,300 TWh in 1990 to under 800 TWh today, as oil became too expensive and inefficient for power generation compared to gas and renewables.

However, Figure 1.11 reveals a significant anomaly: a sharp, temporary spike in production around 2012 caused by the Fukushima nuclear disaster in Japan in 2011, which forced the country to idle its nuclear fleet and drastically ramp up oil-fired generation to prevent blackouts (EIA, 2013), creating a visible "tooth" in the global data before the downward trend resumed; additionally, both charts highlight a marked reduction in oil demand and electricity production in 2020 due to the Covid-19 pandemic.

However, another temporary spike in oil-fired electricity generation is evident in 2022. This global increase was a direct consequence of the energy crisis triggered by the Russian invasion of Ukraine. Record-high natural gas prices, combined with Russia's decision to curtail pipeline flows to the European Union, forced a significant shift toward oil as an emergency alternative (IEA, 2022).

Comparing the outlooks, the WEO 2010 (Current Policies) envisioned a world of persistent need for oil where demand would skyrocket to over 5,500 Mtoe by 2050, driven by population and economic growth with prices reaching $135/barrel by 2035 to balance supply. In the 2010 New Policies Scenario, demand was projected to grow steadily to about 4,550 Mtoe by 2035 with an import price of $113/barrel; notably, all this growth was expected to come from non-OECD countries, 57% from China alone, while OECD demand was set to fall by over 280 Mtoe.

The 2010 outlook noted that while economic activity remained the principal driver, the oil intensity of GDP had fallen, with each 1% increase in GDP accompanied by only a 0.3% rise in demand and anticipated that unconventional sources like Canadian oil sands would meet about 10% of world demand by 2035. Conversely, the WEO 2010 450 Scenario predicted demand would peak around 4,175 Mtoe in 2020 and fall to 3,816 Mtoe by 2035 due to radical policy action (IEA, 2010).

Moving to the present, the WEO 2024 projections reflect a transformed landscape where demand in 2023 surpassed the 2019 peak to reach 4,585 Mtoe, driven by a recovery in aviation and a surge in petrochemicals, with supply growth met by non-OPEC sources like US tight oil.

According to the Stated Policies Scenario (STEPS), global oil demand is projected to peak before 2030 at just under 4,700 Mtoe, before entering a plateau or a gradual decline to approximately 4,200–4,300 Mtoe by 2040. This shift is primarily driven by the rapid adoption of electric vehicles (EVs). Having already displaced 47 Mtoe of demand, EV sales are expected to avoid an additional 550 Mtoe of growth by 2035, leading to a net contraction of 115 Mtoe in road transport oil use.

Geographically, the outlook is divided: while India records the highest demand growth (+1.9 mb/d) and China becomes the world's largest consumer by 2030, advanced economies will see an accelerating decline. This is underscored by EV market shares, which are projected to reach 90% in Europe and 70% in North America by 2035

Despite these shifts, a massive gap remains between current trajectories and climate goals. In the Announced Pledges Scenario (APS), oil demand is projected to fall by 17% by 2035, supported by enhanced recycling and the addition of 135 million more EVs than in STEPS. However, the Net Zero Emissions (NZE) scenario necessitates a far more drastic contraction, requiring demand to plummet to under 2,000 Mtoe by 2040, a target that rely on achieving nearly 100% EV sales shares in advanced economies (IEA, 2024).

In the power sector, the clear alignment across all modern scenarios suggest that oil-fired electricity is a dying technology, destined to fade to near-zero levels by 2040-2050.

1.6.7. Gas Energy Demand and Gas Electricity Production

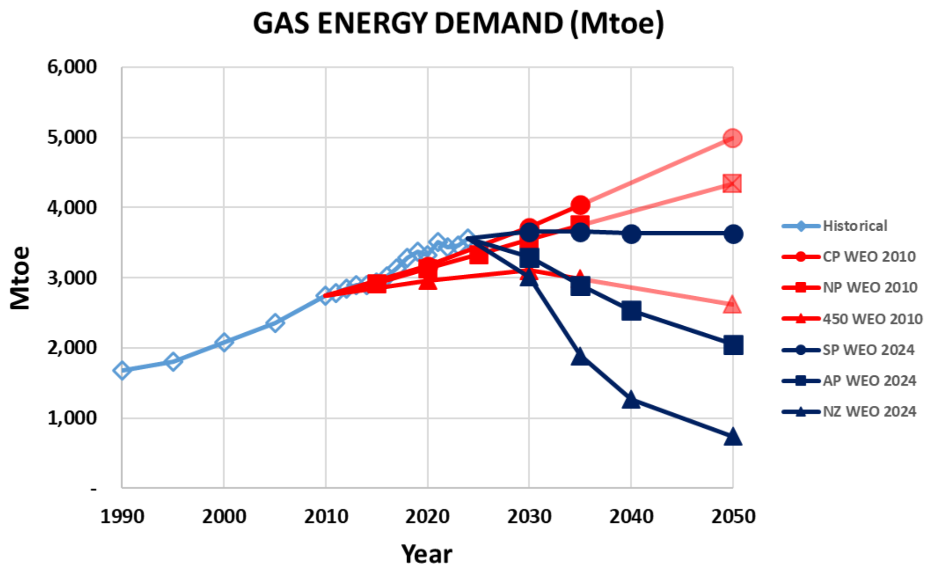

Figure 1.12: Gas Energy Demand

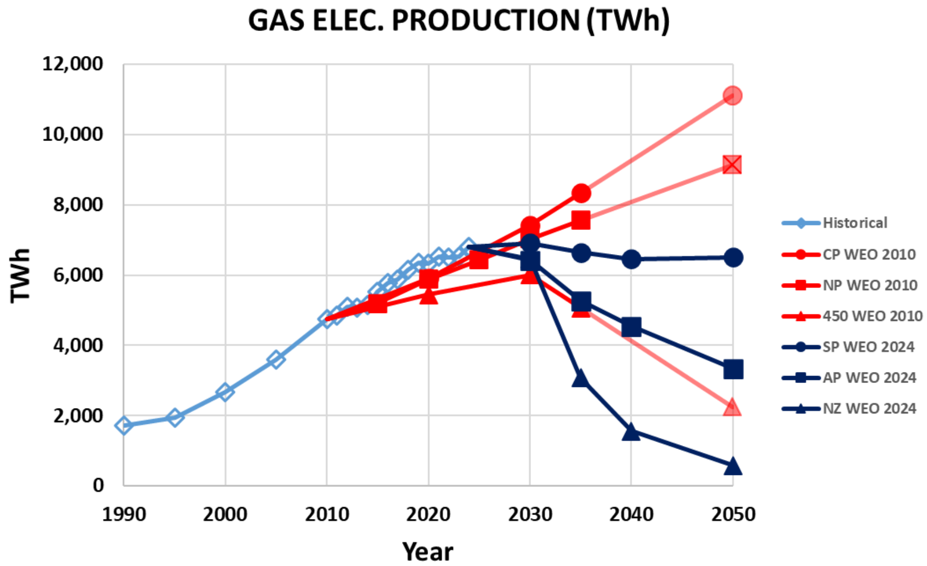

Figure 1.13: Gas Electricity Production

Figure 1.12 and Figure 1.13 describe natural gas energy demand and electricity production respectively, reporting the historical trend and the WEO 2010 and 2024 projections. Unlike coal or oil, the historical trend for natural gas (light blue line) shows a nearly perfect linear trend from 1990 to the present day. In addition, electricity production has tripled from approximately 2,000 TWh in 1990 to over 6,000 TWh today. This growth took place because gas is a flexible source to balance variable renewables and is a cleaner source in replacing coal, in fact, gas emits approximately half the CO_2 per unit of electricity produced compared to coal. In 2010, gas was defined as the "bridge fuel"; despite a 2% drop in demand in 2009 due to the financial crisis (the biggest since the 1970s), the WEO 2010 Current Policies and New Policies scenarios predicted robust growth.

In the New Policies Scenario, demand was set to reach 3,750 Mtoe by 2035 (a 44% increase over 2008), while the Current Policies scenario assumed 4,040 Mtoe. It was anticipated that non-OECD countries would account for 84% of this increase, with China growing at nearly 6% annually and the Middle East increasing its gas-fired generation to over 1,000 TWh. In OECD countries, while growth was expected to slow to 0.9% per year (compared to the rapid >6% expansion since 1990), gas was projected to maintain a constant ~21% share of global electricity generation. Even the climate-ambitious "450 Scenario" considers gas as the only fossil fuel with higher demand in 2035 than in 2008, peaking only in the late 2020s (IEA, 2010). Notably, the actual historical trend has exceeded even these ambitious 2010 projections.

In these years, instead, the energy landscape has been reshaped by the invasion of Ukraine. Russian exports have been reduced from a record 225 Mtoe in 2021 to just 117 Mtoe in 2023. While this shock caused EU demand to drop by 20%, global demand rose by 0.5% in 2023, driven by consumption in China and the Middle East. Looking ahead, a massive wave of new supply is imminent, with 243 Mtoe of LNG capacity currently under construction alongside 180 Mtoe of upstream projects.

In the Stated Policies Scenario (STEPS), natural gas demand is projected to peak around 2030 at just over 3,600 Mtoe, followed by a marginal decline through 2050 driven by the expansion of renewables and electrification. However, the gap between current pledges and the requirements for climate safety remains vast. While the Announced Pledges Scenario (APS) anticipates a 17% reduction in demand by 2035, the Net Zero (NZE) pathway necessitates a precipitous decline: gas consumption must decrease by approximately 5% annually until 2035, with the rate of decline accelerating to 6% thereafter. While gas still plays a role in displacing coal in the short term, its use in electricity generation must reach near-zero levels by 2050 to remain consistent with the NZE trajectory (IEA, 2024).

1.6.8. Solar PV Electricity Production

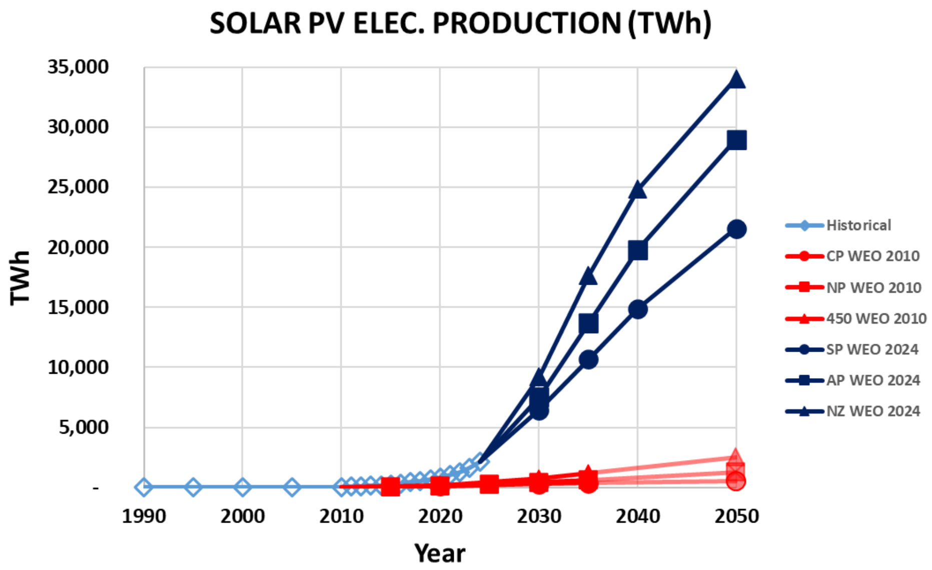

Figure 1.14: Solar PV Electricity Production

Figure 1.14 illustrates the electricity production from solar photovoltaics (PV) comparing the historical trend with the projections from the WEO 2010 and 2024. The first concept to underline is the huge difference in scale between the red lines (2010 vision) and the dark blue lines (2024 vision): in 2010, the red lines are almost crushed against the X-axis, appearing irrelevant, while in 2024, the blue lines increase with a nearly vertical slope, reaching values up to 35,000 TWh. This discrepancy exists because, in 2010, solar was too expensive and considered as a marginal technology. Even in the most optimistic scenario of that time (the "450

WEO 2010," represented by the light red triangle), it was predicted that solar would produce approximately 2,500–3,000 TWh by 2050 (extrapolating results from 2035).

The historical trend, however, has far surpassed all forecasts formulated in the WEO 2010. Analyzing its trajectory, is possible to notice that the world has reached today, 25 years ahead of schedule, what was believed in 2010 to be the "maximum optimistic scenario" for the mid-century. Specifically, the WEO 2010 New Policies Scenario projected that electricity produced from solar PV would increase from 12 TWh in 2008 to just 630 TWh in 2035 (around 2% of global electricity), with installed capacity growing from 15 GW in 2008 to 410 GW in 2035. Of this projected capacity, a little more than half was expected to be installed in buildings (meeting around 4% of their demand), while the remainder was for large-scale generation and some rural electrification projects; notably, over 160 GW (40% of the world total in 2035) was projected to be installed in non-OECD Asia, particularly in China and India (IEA, 2010).

By 2024, the trend has completely flipped: solar has become the cheapest source of electricity in history in most of the world. In the WEO 2024 Stated Policies (STEPS) scenario, even without new climate laws and driven solely by economic inertia and convenience, solar production is set to rise to over 21,000 TWh in 2050, almost 10 times what was thought possible in 2010.

In fact, solar PV capacity additions increased by over 80% in 2023 to reach a new record of 425 GW. China was responsible for over 60% of all capacity additions (increasing deployment 2.5-times), largely because the rapid expansion of manufacturing resulted in a 50% reduction in PV module costs since December 2022. Advanced economies accounted for most of the remaining growth in 2023, with nearly 60 GW added in the European Union and over 30 GW in the United States, while the rest of the world added over 70 GW. Looking forward, solar PV capacity additions are set to expand by almost 60% in the STEPS by 2035, double in the Announced Pledges Scenario (APS), and increase 2.5-fold in the Net Zero Emissions (NZE) Scenario.

Today, solar PV generates just over 5% of total electricity, but its share is set to rise to 17% by 2030, playing a crucial role in meeting the COP28 pledge to triple renewable capacity. By 2035, solar PV is projected to overtake coal-fired and gas-fired generation to become the main source of electricity, providing 25% of total generation in the STEPS, 30% in the APS, and 35% in the NZE Scenario. Naturally, this rapid rise increases the need for power system flexibility to ensure electricity security (IEA, 2024).

1.6.9. Wind Electricity Production

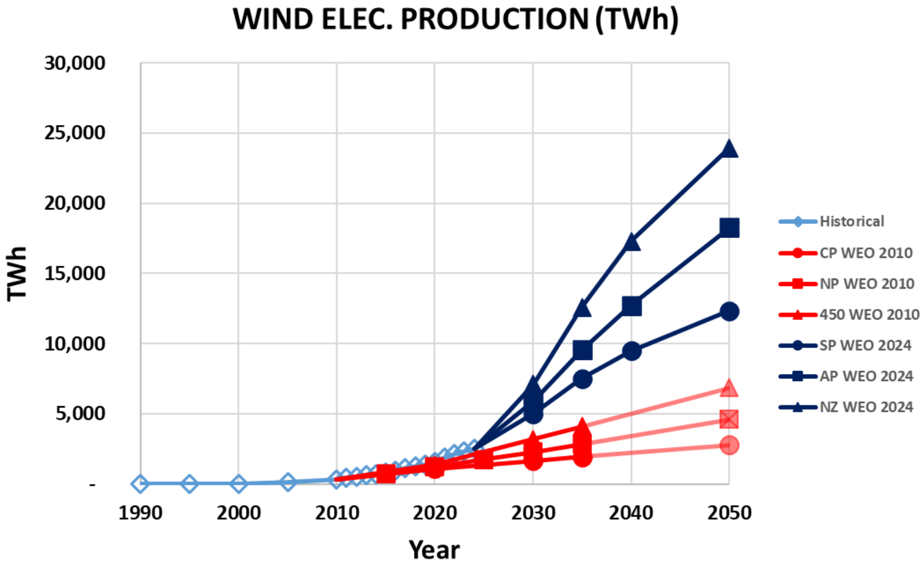

Figure 1.15: Wind Electricity Production

Figure 1.15 illustrates the historical trend and the projections formulated in the WEO 2010 and 2024 editions regarding electricity production from wind. Observing the historical line, it is evident that actual growth has surpassed all predictions made in WEO 2010 for the comparison years; specifically, a marked acceleration is visible starting from 2010, driven primarily by the explosive growth of the wind sector in China. In 2010 wind was viewed as a mature technology but with perceived limits to its scalability. In the WEO 2010 New Policies Scenario, wind power (onshore and offshore) was projected to supply 8% of global electricity by 2035, up from just 1% in 2008, with generation increasing by a factor of 13 and installed capacity rising from 120 GW to over 1,000 GW. This projection continued the strong trend of that decade, where in 2009 alone, 38 GW were added worldwide (14 GW in China, and 10 GW each in the EU and US), with these three regions expected to account for 70% of global capacity by 2035. While onshore wind was expected to dominate, the scenario anticipated offshore capacity growing from a mere 1.5 GW in 2008 to almost 180 GW in 2035. However, all the projections underestimate the real trend. The normative climate scenario of 2010 (the "450 Scenario," represented by light red triangles) aimed to reach about 7,000 TWh in 2050, that is approximately half of what is projected in the "base" Stated Policies (STEPS) scenario of 2024 (IEA, 2010).

In the 2024 outlook, the trend has shifted: wind is now recognized as a fundamental renewable source, alongside solar, for sustaining the global grid. Worldwide wind capacity additions increased by over 50% to a record 116 GW in 2023, surpassing the previous 2020 high. Onshore projects dominated with 107 GW (92% of the total), and China led by far, adding 76 GW or 66% of the global total. In contrast, expansion in advanced economies was slower, with the EU adding only 15 GW and the US adding just over 6 GW (down from >14 GW in previous years). Despite constraints like financing costs and grid connection delays in emerging markets, wind is today the largest source of variable renewable electricity with 1,000 GW installed generating over 2,300 TWh. It plays a central role in the COP28 pledge to triple renewable capacity: in the 2024 STEPS, wind becomes the second-largest source of electricity by 2035, with 2,800 GW of capacity and 7,500 TWh of generation, rising to 12,000 TWh by 2050, nearly double the 2010 "green" hope. In the more ambitious scenarios, capacity rises even faster by 2035, to over 3,500 GW in the Announced Pledges Scenario (APS) and over 4,500 GW in the Net Zero (NZE) Scenario, with the NZE pathway requiring generation to reach a staggering 24,000 TWh by 2050 (IEA, 2024).

1.6.10. Renewables Electricity Production

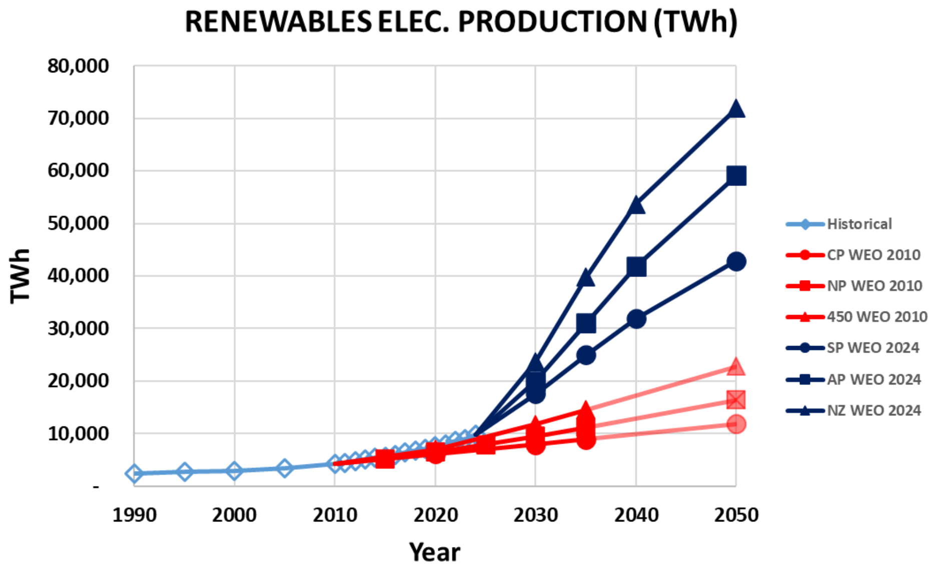

Figure 1.16: Renewables Electricity Production

Figure 1.16 represents the historical trend and the projections from the two Outlooks regarding electricity production from renewable sources. Analyzing the graph is possible to understand that in 2010 renewables were viewed merely as a useful addition rather than a dominant technology. In the WEO 2010 base case (Current Policies), growth was predicted to be slow, reaching only about 12,000 TWh in 2050; even the ambitious "450 Scenario" of that era barely reached 22,000–23,000 TWh.

In the 2024 edition, the trend has shifted entirely: the WEO 2024 base case (Stated Policies - STEPS) already assumed to reach 42,000–43,000 TWh by 2050, nearly double the 450 trajectory of the 2010 edition. Furthermore, the Net Zero (NZE) line in the 2024 outlook is projected to reach over 70,000 TWh in 2050. Considering that the entire world currently consumes about 28,000–30,000 TWh of electricity from all sources combined, the NZE scenario implies that to reach net zero, it necessary not only to replace existing coal and gas plants but more than double of the entire global electrical system. This is necessary because renewable electricity will be required to power sectors that currently run on oil or gas, such as electric vehicles, heat pumps for buildings, and hydrogen production for heavy industry. The historical blue line confirms this shift, showing a curve that is increasing upwards in recent years (2010–2023). In addition, the graph shows that the historical evolution of renewables electricity generation has nearly followed the 450 trajectory at least up to now.

Looking back at the context of the WEO 2010, renewables supplied almost 3,800 TWh in 2008 (19% of total production), a share that had changed only marginally since 2000. At that time, 85% of renewable electricity came from hydropower. While non-hydro sources (biomass, solar, wind, geothermal, marine) were rising slowly, from 2% of total generation in 2000 to 3% in 2008. Between 2000 and 2008, renewables grew by 900 TWh, while coal increased by 2,300 TWh and gas by 1,600 TWh.

Despite this, the WEO 2010 New Policies Scenario projected a tripling of renewable generation to nearly 11,200 TWh by 2035. This was possible by rapidly expanding wind generation, rising from 219 TWh to almost 2,900 TWh, with growth rates of 8% in the OECD and 15% in non-OECD countries, and hydropower, increasing up to 5,500, with 90% of that growth coming from non-OECD countries. Biomass was expected to increase five-fold to 1,500 TWh by 2035, while solar PV and marine energy remain limited.

Regarding the growth in electricity demand between 2008 and 2035, the contribution of renewables varies sharply depending on the scenario. Driven by government support and economies of scale, renewables were projected to meet 28% of this new demand in the Current Policies Scenario, 50% in the New Policies Scenario, and a massive 90% in the 450 Scenario (IEA, 2010).

Moving to WEO 2024, it's necessary first to analyze that in 2023, despite a decline in hydropower output, renewables reached 30% of global generation for the first time, with wind and solar PV together providing 13%, double the level of just five years prior.

In the STEPS, solar PV and wind combined generation is set to nearly triple from 2023 to 2030, accounting for over 90% of electricity supply growth and overtaking coal, which peaks around 2025. By 2035, solar and wind alone will provide over 40% of generation, necessitating modernized grids and expanded flexibility via storage.

In addition, by 2023, 152 countries had set renewable targets, and a pledge to triple capacity, as announced at COP28. Major economies like Korea and India aim to more than double, and Indonesia to more than triple, the role of renewables by 2030. Regionally, in the Stated Policy Scenario, the European Union is set to reach over 70% renewable generation by 2035 (rising to over 80% in the APS), while China is set to obtain two-thirds of its generation from renewables by 2035 (IEA, 2024).

1.6.11. Hydro, Biomass and Geothermal Electricity Production

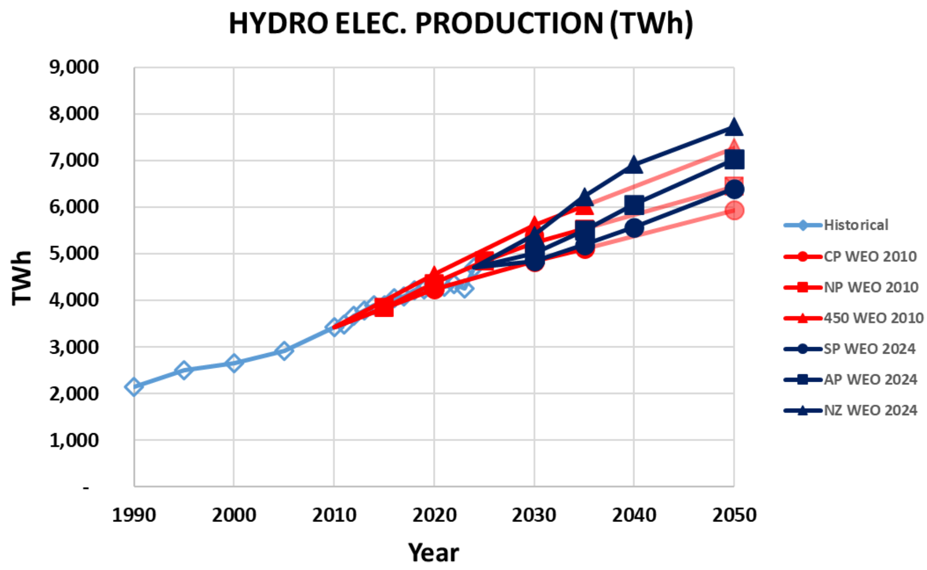

Figure 1.17: Hydro Electricity Production

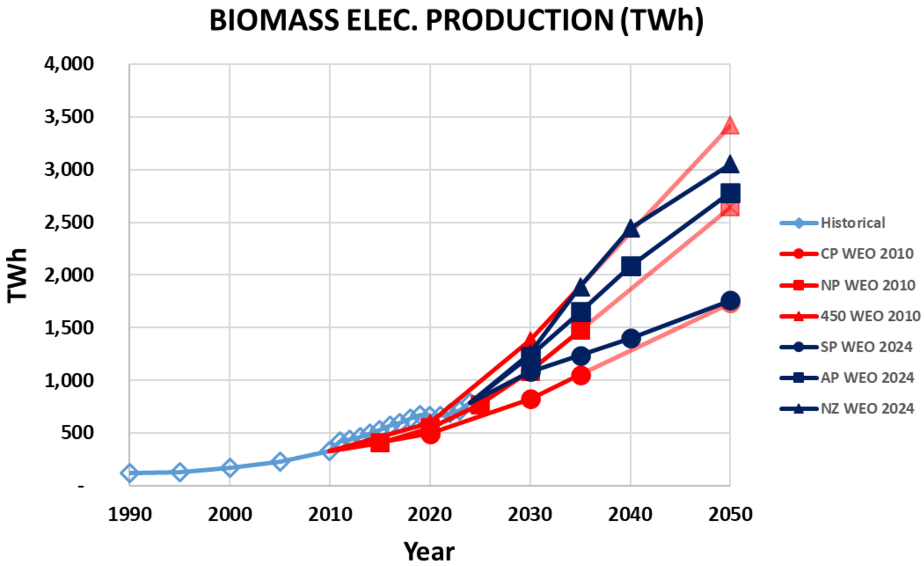

Figure 1.18: Biomass Electricity Production

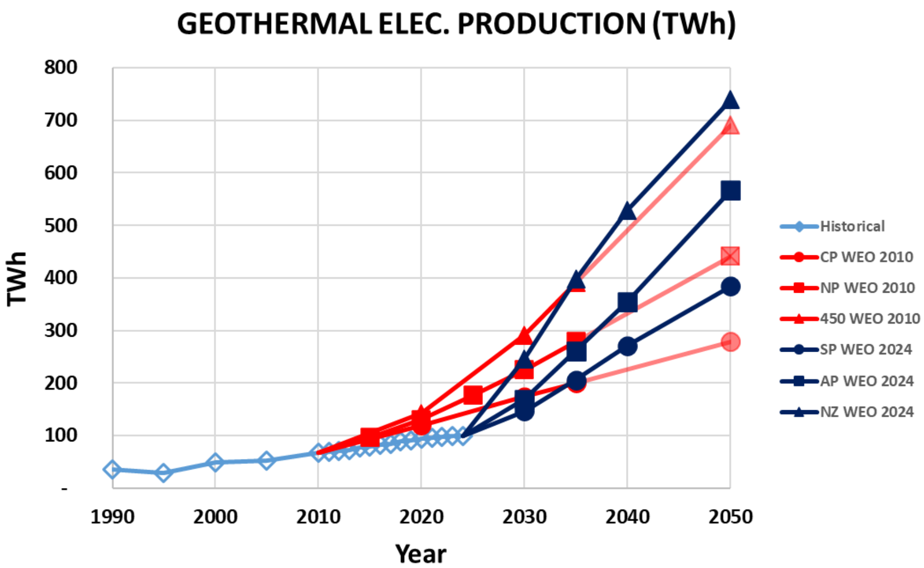

Figure 1.19: Geothermal Electricity Production

Figure 1.17, Figure 1.18, Figure 1.19 represent Hydro, Biomass, and Geothermal Electricity Production. Hydropower is characterized by steady historical growth and a remarkably clustering of projections. Both the 2010 and 2024 outlooks align on a gradual rise to values between 6,000 and 8,000 TWh by 2050, reflecting the physical constraints of a mature technology where geographical limitations prevent exponential expansion. However, the chart reveals a noticeable negative spike in 2022, underling this technology's vulnerability to climate change: that year, severe and historic droughts across Europe, China, and the Americas drastically reduced water levels, limiting hydroelectric generation (International Hydropower Association, 2022).

In contrast, Biomass shows a different trajectory, with production accelerating visibly from 2010 onwards. This sustained increase was driven by strong government policies and incentives, particularly in the EU and China, aimed at decarbonizing the power sector by converting coal plants to biomass and supporting "dispatchable" renewables to balance the grid.

Finally, Geothermal reveals a significant gap between current policy trajectories (STEPS) and necessary climate ambitions (Net Zero). In addition, while the 2010 "450 Scenario" (red triangles) nearly matched modern Net Zero targets, current real-world deployment remains slow (lower than all the 2010 scenarios projections), suggesting that without aggressive new policy support, this dispatchable source will struggle to be largely deployed. In conclusion, for these three renewable sources 2010 and 2024 projections are approximately comparable.

1.6.12. Nuclear Electricity Production

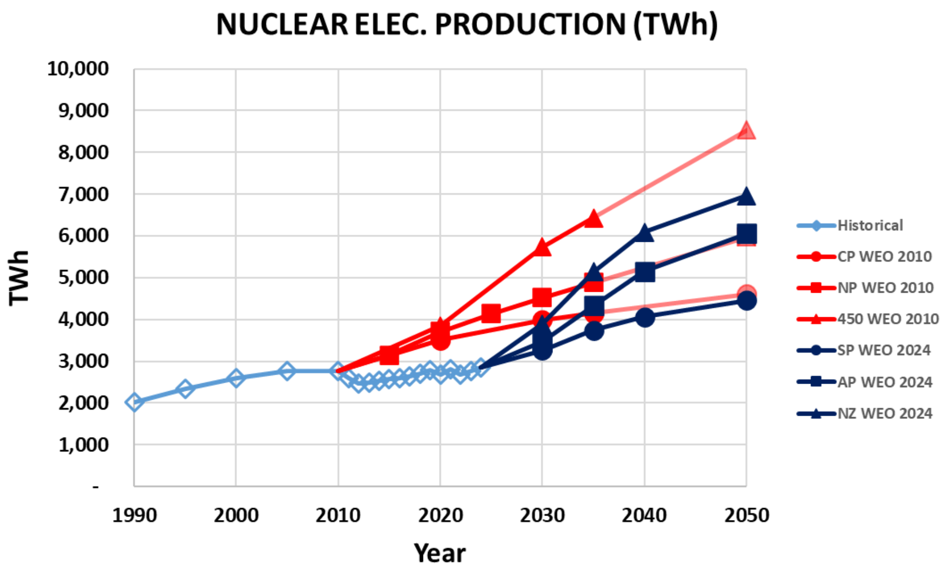

Figure 1.20: Nuclear Electricity Production

Figure 1.20 shows the historical trend and WEOs projections for nuclear electricity production. Exploring the historical line, is possible to notice that production was rising from 1990 up to 2010 before suffering a sudden drop and a near-decade of stagnation due to the Fukushima accident, which led Japan to idle its reactor fleet, Germany to accelerate its phase-out (Energiewende), and many other nations to pause projects. Consequently, real production remained flat for years, below the upward trajectories predicted by all WEO 2010 scenarios.

Regarding the WEO 2010, the "450 Scenario" (red triangles) consider nuclear as one of the primary decarbonization technologies, projecting it to nearly 9,000 TWh by 2050. Instead, in the WEO 2024 Net Zero scenario the target is projected at approximately 7,000 TWh. This downward revision reflects the fact that while nuclear remains valuable, its centrality has been challenged by solar and wind, which have become cheap and efficient. Nevertheless, all modern scenarios (SP, AP, NZ) assume growth rather than decline. The Stated Policies (STEPS) scenario shows production slowly doubling from current levels of 2,500 TWh to roughly 4,500 TWh by 2050, driven by lifetime extensions in the West and massive expansion in China.

It is important to underline that from 2023, policy support has notably risen, over 20 countries pledged to triple global capacity by 2050, with tangible extensions in Belgium, the abolishment of a ban in Switzerland, new builds declared in Sweden and Poland, and reaffirmed commitment in France.

Currently providing 9% of global electricity, nuclear is valued for offering baseload power and grid stability to complement renewables. In 2023, five new reactors (5.5 GW) began operations in Belarus, China, Korea, the Slovak Republic, and the US; combined with 1.6 GW of restarts, this net increase offset 6.3 GW of retirements. This increase continued through the first nine months of 2024 with 4.5 GW connected to the grid and construction starting on seven new reactors (five in China, one each in Egypt and Russia). As of October 2024 62 reactors, totaling 75 GW, are under construction, promising to increase global capacity by nearly 20%. Emerging markets are the main reason of this growth, particularly China, which accounts for 40% of additions in the STEPS and almost 50% in the NZE by 2035, putting it on track to hold the world’s largest nuclear capacity by around 2030. Furthermore, the industry is looking toward Small Modular Reactors (SMRs), currently under development in Canada, France, Japan, Korea, the UK, the US, China, and Russia (IEA, 2024).

1.7. Conclusion of the Chapter

The comparative analysis presented in the previous sections, which evaluated historical data against the projections of the WEO 2010 and WEO 2024 editions, highlights a profound systematic underestimation of renewable energy sources, specifically solar PV and wind, in the earlier 2010 report, a misalignment extensively supported by academic literature identifying several technical and institutional causes for such discrepancies.

(Mohn, 2016) argues that the IEA's 2010 framework suffered from the premature application of an "S-curve" market penetration model, which forced a deceleration in renewable growth that was not justified by real-world market trends, while technological progress was imposed a priori through exogenous coefficients based on expert judgment rather than being determined within the model as a dynamic function of prices and R&D investments.

(Mohn, 2016) further highlights that the model tended to assume a stabilization of investment rates in renewables while these actually continued to rise, suggesting that bias may also arise from institutional "expert judgment" that tends to favour established technologies over disruptive innovations.

(Mohn, 2016), alongside (Teske, 2020), also identifies a "vintage capital" bias, where the 2010 report placed excessive emphasis on the longevity of existing energy infrastructure, making structural transitions appear slower and more expensive than they truly were, an inherent conservatism mainly due to the structure of the World Energy Model (WEM), which functioned as a deterministic and recursive simulation model rather than an optimization model, effectively fixing projections to past trends rather than future innovations.

According to (Mohn, 2016), this modelling system is considered too rigid and insufficiently responsive to sudden shifts or shocks in technology; furthermore, he highlights a lack of transparency regarding key parameters, econometric equations, and diagnostic data, making a complete external evaluation nearly impossible, a factor that also explains why the European modeling phase with OSeMOSYS in this thesis could not rely solely on WEO 2024 data but required assumptions and data from alternative sources.

These modelling errors were exacerbated by the IEA's use of linear growth trends for renewables, which, as (Simões, 2021) point out, ignored the long-term exponential growth patterns established in the industry and highlighted how a fundamental cause of these forecasting misalignments lies in the reliance on "legacy models", referring specifically to the WEM architecture originally conceived for a centralized system dominated by fossil fuels, which exhibit a methodological inertia that makes them ill-suited to capturing disruptive events or the rapid energy transitions required to minimize environmental impacts.

Economically, (Hadi Vatankhah Ghadim, 2025) demonstrate that cost projections for solar and wind were systematically higher than market realities because the IEA relied on obsolete data and learning rates that failed to capture rapid technological cost declines, a "cost pessimism" further distorted by the application of arbitrary discount rates that artificially inflated the Levelized Cost of Electricity (LCOE) for renewables, providing a skewed economic basis for fossil fuel expansion.

Beyond methodology, (Mohn, 2016) , (Labban, 2012), and (Matthieu Metayer, 2015) suggest that the IEA's institutional conservatism may reflect the interests of industrialized member states and the fossil fuel industry; because WEO reports require approval from OECD governments, many of which depend on conventional energy revenues, the projections were often biased toward maintaining the status quo.

Ultimately, the analysis of these results confirms that the limitations of the model, biased inputs, and conservative assumptions determined the underestimation of renewables in the WEO 2010.

These findings serve as a vital lesson for the OSeMOSYS European model used in this research, demonstrating that assumptions regarding technology phase-outs, structural constraints, and investment limits exert a profound influence on final energy trajectories, while also revealing that the energy mix is guided by interests beyond pure economics, such as national security, independence, and the decisive role of policy frameworks.

2 Energy Modelling Frameworks: Classification

In this second chapter, the main energy model classifications used for energy capacity planning and dispatch operation are analyzed. Energy models are mathematical, formal representations of the energy system, that consider the relationships between energy demand, resources, conversion technologies, infrastructure, costs, and constraints (e.g., technical limits and emissions targets) and are used to explore how the energy system may evolve, under different assumptions, or while satisfying a certain objective function (ScienceDirect, 2026).

2.1. Main classification schemes in the literature

This sub-chapter provides a systematic review and analysis of energy model classifications, analyzing their evolution from foundational paradigms to the most recent frameworks. This literature-based research is essential for identifying the taxonomical criteria that define these tools; by understanding how models are categorized, it is possible to understand their inherent technical characteristics and the specific attributes that distinguish one modelling approach from another. While this analysis is not intended to be exhaustive, it synthesizes the most prominent methodologies currently established in literature. As will be observed, these classifications are intrinsically linked, they frequently overlap and build upon one another, sharing similar classification criteria.

2.1.1. Van Beeck: "nine ways" to classify energy models

(Beeck, 1999) in a review paper proposed nine different ways of classifying energy models, based on the main model distinctions. In addition, this classification is the basis for the other proposed energy model classifications.

The nine ways include:

1. General and Specific Purposes of Energy Models.
2. The Model Structure: Internal Assumptions & External Assumptions
3. The Analytical Approach: Top-Down vs. Bottom-Up
4. The Underlying Methodology
5. The Mathematical Approach

6. Geographical Coverage: Global, Regional, National, Local, or Project
7. Sectoral Coverage
8. The Time Horizon: Short, Medium, and Long Term
9. Data Requirements.

It is important to underline that the classification categories outlined above (methodology, mathematical approach, geographical, sectoral, and temporal coverage) are neither exhaustive nor mutually exclusive. Modern energy models combining different characteristics and properties to address specific research questions.

General and Specific Purposes

General purposes describe how an energy model relates to the future. Three broad purposes can be distinguished:

- Forecasting models extrapolate recent trends and historical patterns into the near term, if key drivers remain stable over the projection period.
- Scenario analysis explores alternative futures by comparing a reference ("business-as-usual") case with a set of different scenarios defined by explicit assumptions on technology, resources, policy and socio-economic drivers.
- Back casting models start from a desired long-term end state and work backward to identify the technological, structural and policy changes required to reach it.

Specific purposes refer to the core aspect each model is designed to analyze.

- Energy demand models explain how energy use evolves for the whole economy or for individual sectors as a function of drivers such as population, income, prices, technologies and policy.
- Energy supply models represent the technical configuration and operation of the supply system and assess if and how demand can be met, often through least-cost optimization to identify an economically efficient supply mix.
- Impact models quantify the effects of technologies or policies, covering economic, social and environmental dimensions (e.g., costs, distributional effects, employment, emissions). The goal is to evaluate what happens if a given option is implemented.
- Appraisal models compare and rank alternative options with predefined criteria, most commonly technical performance and cost efficiency, but also reliability and sustainability objectives.

Model Structure: Internal Assumptions & External Assumptions

Energy models differ also in their model structure, especially regarding the assumptions. Assumptions are split in internal assumptions, determined within the model and external assumptions, imposed by the user.

In the paper review (Beeck, 1999) describes model structure with four independent dimensions and each range from "less" to "more," and any given energy model can be positioned along these four axes:

- Degree of endogenization, namely the extent to which key drivers are generated by the model's equations rather than being defined exogenously. In this case forecasting models often endogenize behavioral responses, while scenario-based and back casting typically rely more on externally defined behavioral and structural assumptions.
- Level of detail of the non-energy economy, i.e., how explicitly the model represents macroeconomic mechanisms such as investment, trade, non-energy consumption and income distribution.
- Details of energy end-uses, regarding the granularity with which final energy services and end-use technologies are represented (e.g., appliances, process heat, mobility).
- Details of energy supply technologies, which determines how well the model can analyze fuel substitution, technology deployment and system design; more aggregated approaches often treat technology in a stylized way, which limits the comparison of specific supply options.

Within this framework, a large share of the data needed to run an energy model are provided through external assumptions, defined by the user. Typical exogenous inputs include population and economic growth, assumptions on demand and supply evolution, price and income elasticities, and existing tax system.

In practice, models lie on a continuum between two extremes: if all parameters are exogenous, the model is merely a computational device (albeit highly flexible); if none are exogenous, the model is infeasible. Most energy models therefore adopt a mixed approach, with some parameters set externally and others determined endogenously.

Analytical Approach: Top-Down vs. Bottom-Up

An important distinction in energy modelling is between top-down and bottom-up approaches, as in Figure 2.1. Even if both are used for energy modelling, they often produce different results, because they consider technology detail, decision-making behavior, and market adjustment mechanisms in different ways. This contrast is sometimes framed as an “economic” (top-down) versus “engineering” (bottom-up) perspective, with top-down approaches often associated with more “pessimistic” assessments of adjustment costs and bottom-up approaches with more “optimistic” technology-driven opportunities.

Top-down models represent the energy system within a highly aggregated macroeconomic framework, focusing on interactions between the energy sector and the rest of the economy. Policy impacts are typically assessed through changes in sectoral outputs, prices, and economic indicators such as GDP. For this reason, top-down models are generally used for evaluating market-oriented policies (e.g., carbon taxes) and economy-wide effects. They rely on highly aggregated economic data and represent behavior through relationships that are estimated from historical patterns (for instance, how consumers and firms exchange energy use when prices or incomes change). They are generally used for short- to medium-term predictive exercises, especially when it is reasonable to assume continuity of past relationships over the projection period. Typical top-down families include input–output models, macro econometric models, and computable general equilibrium (CGE) models. However, their main limitation is that the representation of energy technologies is often not explicit: technology is frequently treated as a “black box” within production functions, which constrains the ability to analyze detailed technology substitution and specific supply options.

Bottom-up models, by contrast, describe the energy system using disaggregated technological data, representing supply and end-use technologies are explicitly described with technical performances, investment costs, operating costs, and efficiencies. This structure makes them particularly valuable for exploring how different technology mix can deliver energy services, and they tend to reflect technical potential more than observed market adoption patterns. This makes bottom-up models particularly useful for capacity expansion planning, technology substitution analysis, and the identification of least-cost technology pathways. Many bottom-up models adopt a partial equilibrium perspective: demand trajectories are often specified exogenously and feedback between the energy sector and the wider economy is limited.

Within the bottom-up family, a further distinction is often made between descriptive and prescriptive approaches. Descriptive models aim to approximate observed decision-making by accounting for non-cost factors and real-world constraints (e.g., preferences, risk, capital constraints, market barriers), while prescriptive models estimate what could be achieved under idealized conditions, typically by minimizing explicit system costs or assuming adoption of the most efficient options. In practice, descriptive approaches tend to obtain less optimistic transitions than prescriptive ones.

Over time, the distinction between top-down and bottom-up modelling has become less rigid. Hybrid models combine macroeconomic feedback with technology-rich representations, aiming to overcome the respective limitations of the two approaches. Hybrid models can be obtained with soft linking, where outputs from one model are iteratively used as inputs to another, or through hard linking, where components are coupled and solved jointly. Integrated Assessment Models (IAMs) represent an important example of hybrid architectures, combining energy, economy and climate components to assess emission trajectories and mitigation pathways (Guivarch, 2022).

Overall, the differences can be summarized as follows: top-down models are strong in capturing market behavior and economy-wide interactions but weaker in detailed technological representation; bottom-up models provide technology-rich system detail and are well suited to exploring long-term transitions, but they may simplify macroeconomic feedback and real-world adoption frictions. This trade-off explains why the two approaches can produce different estimates of costs, technology uptake, and efficiency potentials, and why hybrid approaches are often used when both perspectives are needed.

Top-Down Models	Bottom-Up Models
use an “economic approach”	use an “engineering approach”
give pessimistic estimates on “best” performance	give optimistic estimates on “best” performance
can not explicitly represent technologies	allow for detailed description of technologies
reflect available technologies adopted by the market	reflect technical potential
the “most efficient” technologies are given by the production frontier (which is set by market behavior)	efficient technologies can lie beyond the economic production frontier suggested by market behavior
use aggregated data for predicting purposes	use disaggregated data for exploring purposes
are based on observed market behavior	are independent of observed market behavior
disregard the technically most efficient technologies available, thus underestimate potential for efficiency improvements	disregard market thresholds (hidden costs and other constraints), thus overestimate the potential for efficiency improvements
determine energy demand through aggregate economic indices (GNP, price elasticities), but vary in addressing energy supply	represent supply technologies in detail using disaggregated data, but vary in addressing energy consumption
endogenize behavioral relationships	assess costs of technological options directly
assumes there are no discontinuities in historical trends	assumes interactions between energy sector and other sectors is negligible

Figure 2.1: Top-Down vs Bottom-Up (Beeck, 1999)

The Underlying Methodology

Energy models can also be classified by their underlying methodology, related to the analytical technique used to describe system behavior and generate results. The following sections outline the primary methodologies utilized in energy system modelling:

- Econometric models apply statistical methods to quantify relationships observed in historical data (e.g., correlations between energy use, prices, income, capital, and labor) and then project them into the future. They are typically used for short- to medium-term projections. They generally do not explicitly represent specific technologies and assume stable observed historical patterns.
- Trend analysis projects aggregate indicators, such as energy intensity or energy-per-capita trends, forward with lower data requirements compared to econometric models. They are generally not used to evaluating policies involving deep technological shifts, or complex energy-economy feedback.
- Macroeconomic Input–Output (IO) Models: These represent the economy as a set of interlinked sectors using IO tables and fixed technical coefficients. They are valuable for assessing how external shocks or specific policies propagate through production chains, assuming fixed input proportions and representative 'average' technology for each sector.
- Equilibrium Models evaluate policy impacts by solving for prices and quantities that clear markets, these can be classified in:
  - Partial Equilibrium, that focuses on a subset of markets (e.g., strict energy supply and demand).
  - General Equilibrium (CGE), that represents simultaneous equilibrium across all markets and sectors. They are generally used for mitigation policy assessment, but they typically offer limited technological detail.
- Optimization Models determine system outcomes by maximizing or minimizing an objective function (commonly total system cost, welfare, or emissions) subject to technical, resource, and policy constraints. They are generally used for capacity expansion planning and long-term trajectories analysis selecting the best technology mix endogenously.
- Simulation Models reproduce system evolution based on a predefined set of rules and assumptions and are generally used for 'what if' scenario analysis, focusing on the consequences of different policy or technological choices. Simulation models may be static (providing a snapshot of a single target year) or dynamic (where the system's future state is path-dependent and influenced by prior accumulation).
- Back casting Methods, compute trajectories by starting from a desired future end-state and working backward to identify the technological, structural, and policy changes required to reach it. Back casting is frequently used to

construct normative scenarios and to test the feasibility of target-consistent trajectories under specific constraints.

- Spreadsheet Models (Toolboxes) that are adaptable "toolkits" characterized by modular templates and building blocks allowing users to define custom frameworks based on specific needs. They are particularly valuable for rapid exploratory analysis, but their validity is highly sensitive to user expertise.
- Multi-Criteria Approaches, evaluate scenarios across multiple competing dimensions simultaneously (e.g., cost, reliability, emissions, equity, social acceptance). They allow for the combination of quantitative outputs with qualitative judgments, making trade-offs explicit.

The Mathematical Approach

Energy models can be further categorized based on the specific mathematical procedures or algorithms employed to solve them. While hybrid approaches combining multiple techniques are increasingly common, the literature identifies three primary foundational methods:

- Linear Programming,
- Mixed Integer Programming, and
- Dynamic Programming.

As defined by (Slesser, 1982), Linear Programming is a mathematical technique used to determine the optimal allocation of resources to maximize or minimize a specific objective function (e.g., cost or profit) subject to a set of operational constraints. A defining characteristic of LP is that all relationships between variables must be expressed as linear equalities or inequalities. In energy modelling, LP is frequently used to determine the most cost-effective mix of inputs and outputs given exogenous prices.

However, this approach has significant limitations:

- Constant Coefficients: It assumes constant returns to scale, meaning it cannot inherently model economies of scale or complex non-linear behaviors.
- LP solvers tend to use the cheapest resource exclusively up to its capacity limit before switching to the next alternative. This "all-or-nothing" logic can lead to abrupt, unrealistic shifts in the solution in response to minor changes in input parameters (Schrattenholzer, 1991).

Mixed Integer Programming is an extension of LP achieving a greater granularity in representing technical properties. The primary advantage of MIP is its ability to use integer and binary (0/1) variables, allowing the model to simulate discrete choices such as "Yes/No" investment decisions.

In the context of energy systems, MIP is generally used for capacity expansion planning, such as whether to construct a specific power plant, how many units to install, or which unit sizes to select. By introducing discrete variables into the formulation, MIP can accurately capture fixed costs, minimum operating levels, and startup/shutdown decisions, which continuous LP variables cannot realistically represent (Schrattenholzer, 1991).

Dynamic Programming is a technique used to solve complex optimization problems by decomposing them into a sequence of simpler, nested sub-problems. The big initial problem is solved by finding the optimal solution for each sub-problem sequentially. In energy modelling, this approach is particularly used to evaluate the optimal growth path or investment trajectory over time, since each decisions influence the subsequent steps.

Geographical coverage

Geographical coverage defines the spatial scale of the analysis and characterizes the structure of the model. Is it possible to distinguish:

- Global and Regional Models represent the entire world economy or energy system, while regional models typically cover multi-national aggregates (e.g., the EU-27 or OECD). These frameworks generally require highly aggregated data, and they often adopt a simplified representation of the physical energy system.
- National Models treat global market conditions as exogenous variables but model major domestic sectors endogenously. They frequently employ hybrid approaches, utilizing econometric methods for short-term projections and General Equilibrium (CGE) frameworks for long-term analysis.
- Local and Project-Level Models**.** Local models focus on sub-national entities (such as administrative regions or urban areas), while project-level models analyze specific sites or infrastructures. Unlike global models, these typically adopt bottom-up approaches with highly disaggregated data, allowing for detailed technological and spatial representation.

Sectoral Coverage

Sectoral coverage determines if a model analyses a single specific domain or the interactions across multiple economic sectors. Is it possible to distinguish:

- Multi-Sectoral Models that focus on the interactions between different sectors of the economy (e.g., energy, manufacturing, services), capturing broader economic feedback.
- Single-Sector Models provide detailed insights exclusively into the energy field. In these models, links to the rest of the economy are absent or represented in a highly simplified way through exogenous drivers.

Time Horizon

Time horizons in energy modelling can be classified as:

- Short Term: Periods of 5 years or less.
- Medium Term: Periods between 3 and 15 years.
- Long Term: Periods exceeding 10 years (often extending to 20–50 years for climate transition analysis).

Data Requirements

Energy models are inherently data intensive. The specific requirements depend on the model's structure but can generally be classified as:

- Type: Quantitative (cardinal) versus Qualitative (ordinal).
- Granularity: Aggregated versus Disaggregated (depending on the chosen spatial and technological resolution).

2.1.2. Energy Model Classification by Sathaye and Shukla

Another classification is the one proposed by (Shukla, 2013), establishing a primary distinction between bottom-up and top-down approaches, further subdividing them based on their methodological foundations and theoretical underpinnings:

- Bottom-Up Models: These are segmented into optimization models, which seek the most cost-effective technology pathways under specific constraints, and accounting models, which focus on detailed physical energy flows and stock-taking.
- Top-Down Models: These are categorized into macroeconomic models, which analyze aggregate economic trends and cycles, and computable general equilibrium (CGE) models, which explore inter-sectoral interactions and the systemic impacts of policy changes across the entire economy.

Beyond these methodological distinctions, this classification framework incorporates the temporal horizon and geographical coverage of the models. This allows for the characterization of tools based on their ability to provide either short-term granular forecasts or long-term strategic scenarios, as well as their spatial scope, ranging from local or national assessments to comprehensive global scales.

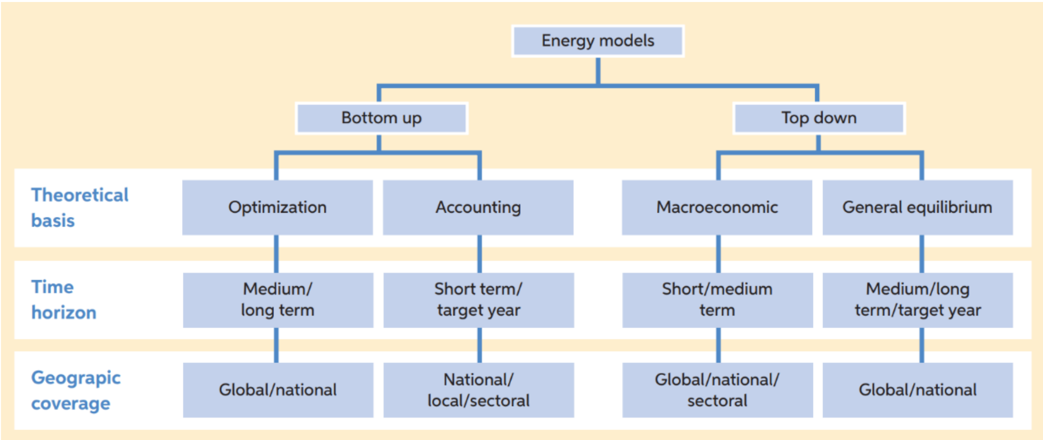

Figure 2.2: Energy Model Classification (Painuly, 2021)

2.1.3. Energy Model Classification by Ringkjøb, Haugan and Solbrekke

Another model classification is the one proposed by (Hans-Kristian Ringkjob, 2018), which categorizes energy models based on three fundamental dimensions: accessibility and availability, general logic and spatiotemporal resolution and techno-economic parameters and components.

In the paper 75 modelling tools, currently used for analyzing energy and electricity sector are presented, evaluating them according to the three comprehensive dimensions:

1. Availability: Classifying models in commercial, free demo version, free, open source, free academic version, unknown, free for academic purpose and upon request.
2. General logic and spatial-temporal resolution: including purpose, approach, methodology, temporal resolution, modelling horizon and geographical coverage of the model.
3. Technological and economic parameters: classifying models according to conventional and renewable generation technology, storage, grid, commodities, demand sector, demand response, demand elasticity costs, market and emissions that can be included and represented in the energy model.

Following the framework proposed, energy models can be categorized based on their purpose into four primary classes:

- Power System Analysis Tools: These instruments are designed for high-fidelity technical assessments. They provide a granular analysis of electrical grids, focusing on steady-state power flows, fault level assessments, and dynamic stability.

- Operation Decision Support: These tools are optimized for short-term horizons. Their primary function is to optimize the operational dispatch and scheduling of the energy system to meet demand efficiently.
- Investment Decision Support: These models focus on long-term capacity expansion and infrastructure investment. Within this category, a fundamental distinction is made regarding the temporal perspective:
    - Myopic Approach: Investments are determined sequentially, where decisions for a specific period are based solely on the information available at that time.
    - Perfect Foresight: The model optimizes the system across the entire study horizon simultaneously, operating under the assumption that all future parameter changes (e.g., fuel prices, policy shifts) are known a priori.
- Scenario Tools: These are utilized to evaluate the long-term impact of energy policies and to explore diverse future pathways within the energy and electricity sectors.

Beyond their primary purpose, the framework distinguishes models by their analytical approach and mathematical methodology:

- Approach: Models are characterized as Top-down (focusing on macroeconomic indicators), Bottom-up (detailing individual technologies and technical components), or Hybrid.
- Methodology: The underlying mathematical structure is categorized into Simulation (describing system behaviour), Optimization (finding the best solution under constraints), or Equilibrium models (balancing supply and demand across multiple markets).

The spatiotemporal resolution is a critical dimension of the framework, defining the inherent limitations of the processes that can be accurately represented. The choice of the most appropriate resolution involves a fundamental trade-off between technical detail and computational feasibility.

- Temporal Resolution: The discretization of time varies significantly depending on the model's purpose. It ranges from milliseconds, necessary for capturing transient phenomena and dynamic stability in technical power system tools, to several decades in macroeconomic equilibrium models focused on long-term transitions. Furthermore, time-steps can be either fixed (uniform) or user-defined as inputs to focus on specific critical periods.

- Geographical Resolution: The spatial scope can range from a single project or building (micro-level) to a national, continental, or global representation (macro-level).

The alignment of these resolutions with the research objectives is fundamental, in fact, a model with low temporal resolution may fail to capture the challenges of variable renewable energy integration, while excessive geographical detail may lead to a huge increase in computational requirements.

The final dimension of the proposed classification evaluates the internal technical and economic granularity of the models. These properties define the system's complexity and the specific technologies it can represent:

- Generation Technologies:
  - Conventional Generation: This category includes dispatchable sources such as thermal power plants, nuclear energy, and bioenergy.
  - Renewable Generation: Except for tidal and geothermal energy, these sources are non-dispatchable and highly dependent on meteorological conditions. Models account for this variability using historical meteorological data, stochastic methods, or simplified profiles. The framework specifically considers wind, solar PV, solar thermal, Concentrated Solar Power (CSP), hydropower, geothermal, wave, and tidal energy.
- Energy Storage: To mitigate the fluctuations of variable renewable energy (VRE), storage integration is necessary to be included in the model. The framework evaluates the inclusion of technologies such as Pumped Hydro Storage (PHS), hydrogen, thermal energy storage, batteries, and Compressed Air Energy Storage (CAES).
- Grid Representation: While system analysis tools focus on detailed physics grid representation (harmonics and short-circuit analysis), models focus on inter-regional electricity exchanges adopting one of these three approaches, organized in decreasing order of complexity:
  - AC Power Flow: Solves 2N non-linear equations for an N-node grid; it captures reactive power but is computationally intensive.
  - DC (Linearized) Power Flow: Ignores reactive power to reduce complexity. It is widely used in planning as errors are typically

limited to a few percent, except under extreme loading conditions where reactive demand rises sharply.

- Net Transfer Capacity (NTC): A simplified representation of transfer limits between zones or countries. Despite its simplicity, it often yields results comparable to DC power flow for inter-zonal studies.

- Commodities and Sector:
    - Commodities: Beyond electricity, models often incorporate heat and hydrogen as critical carriers for 100% renewable scenarios. Fossil resources are generally grouped under a singular "fuels" category rather than distinguished by individual types.
    - Demand Sectors: The end-use sector is typically disaggregated into Buildings (combining residential and commercial), Industry (which includes agriculture), and Transport.
- Demand Dynamics:
    - Demand Elasticity: Quantifies how energy demand responds to price fluctuations.
    - Demand-Side Management (DSM): Encompasses measures such as energy efficiency and Demand Response (DR), both influencing the use of energy. In modelling, DR is represented either as "negative storage" (deferring demand to later periods) or as a "negative generator" defined by specific capacity and cost parameters.
- Economic and Environmental Modules:
    - Costs: Models account for Capital Expenditures (CAPEX), Operational and Maintenance costs (OPEX), fuel, CO_2 taxes, and balancing costs (e.g., start-up, shutdown, and ramping).
    - Market Modelling: Some models assume perfect competition to balance supply and demand, with others including specific layers such as spot, reserve, and balancing markets.
    - Emissions: Environmental impacts are tracked either through specific pollutants (CO_2, NO_x, SO_x, CH_4) or aggregated using CO_2 equivalents.

As emphasized by (Hans-Kristian Ringkjob, 2018), the primary objective of adopting this classification scheme is to provide a structured methodology that assists the researcher in identifying and selecting the most appropriate model for the specific study. By mapping a tool's capabilities against the requirements of the research, such as the need for specific spatiotemporal granularity or the inclusion of certain techno-economic parameters, this framework ensures that the chosen model is able of answering the research questions. By evaluating 75 distinct tools across the dimensions of availability, logic and resolution, and techno-economic parameters, this framework stands as the most comprehensive and technologically rigorous assessment of the current energy models available.

Consequently, this framework is adopted in the present study as one of the benchmarks to justify the selection of the most appropriate model.

2.1.4. Energy Model Classification by Klemm and Vennemann's

A more recent classification is the one proposed by (Christian Klemm, 2021) that focuses specifically on the modelling and optimization of multi-energy systems (MES) at both district and regional levels. This framework categorizes models based on their methodology, assessment criteria, analytical and mathematical approaches, reusability, and structural and technological details.

The framework distinguishes models based on their core objective and the logic used to represent the system:

- Methodology: Models are classified into Optimization (to define "optimum scenarios" by maximizing or minimizing an objective function), Forecasting (to predict system behaviour under specific conditions), and Back-casting (to develop pathways toward desired future goals).
- Analytical Approach: Tools are divided into Bottom-up (technological detail), Top-down (macroeconomic focus), or Hybrid models.
- Mathematical Approach: The computational engine can range from Linear Programming (LP) and Dynamic Programming to Mixed-Integer Programming (MIP), Stochastic Programming (handling uncertainty and probabilistic elements), and Artificial Intelligence (AI) (including fuzzy logic, neural networks, agent-based models, etc…).

Models can be classified also according to the assessment criteria, essential for guiding the optimization process, and can be categorized into five primary dimensions:

- Financial Criteria: These aim to identify the most cost-effective scenario by evaluating metrics such as annualized capital cost, annual system cost, and payback time. Other key indicators include the annual net profit, total capital costs, total life-cycle cost, and the Levelized Cost of Energy (LCOE).
- Energy Efficiency Criteria: These focus on energy balances throughout the system. Measurement typically includes the use of primary energy, secondary energy, or final consumer (end-user) energy use.

- Environmental Criteria: This category evaluate the ecological footprint of the system. Metrics often include greenhouse gas emissions, air pollutants (such as NO_x or SO_x), freshwater consumption, land use, and noise pollution. Furthermore, it may account for human health impacts and the total percentage of renewable energy penetration.
- Technical Criteria: These assess the physical viability and performance of the energy system, specifically considering factors like safety, availability, reliability, and overall technical feasibility.
- Social and Economic Criteria: This dimension evaluates broader societal impacts, such as regional employment rates, technology-specific job opportunities, and the risk of accidents. It also considers the availability of resources, impacts on local living standards, and foreign trade balances.

While financial, environmental, and energy efficiency metrics are the most prevalent in optimizing Multi-Energy Systems (MES), researchers rarely focus on a single objective. Multi-objective optimization approaches are frequently employed to manage trade-offs between competing goals, like minimizing total system costs while respecting an annual CO_2 emission limit or a minimum required percentage of renewables.

Furthermore, energy models can be categorized according to their structural and technological characteristics into several dimensions:

- Geographic Coverage: This defines the total spatial area under consideration in the energy model, which can range from a single power plant to a global scale.
- Spatial Resolution: This determines the granularity within that geographical coverage, distinguishing between specific nodes (consumer sharp, house, blocks of houses), districts, or nations.
- Temporal Resolution: Specifies the duration of individual time steps, ranging from milliseconds to years. In addition, temporal resolution can be fixed or given by the input data.
- Time Horizon: Represents the total duration of the study, which may span a day, a year, a decade, or the entire lifespan of the components within the system.
- Sectoral Coverage: Identifies the energy sectors integrated into the model, typically electricity, heating and cooling, fossil resources, and various commodities.

- Technical Coverage: Refers to the specific mix of technologies (renewable and conventional generation or storage types) implemented within the model's logic.
- Demand Sectors: Including residential and commercial buildings, industry, agriculture, and mobility.
- Demand-Side Management (DSM): Includes all consumer-side measures designed to improve the energy efficiency of the overall system.
- Change of Properties: This describes the model's ability to account for dynamic variables that evolve over the time horizon, such as fluctuations in costs, demand or the introduction of new components.

In addition, the framework distinguishes models based on their accessibility:

- Open Models: Characterized by public access to their source code, underlying assumptions, and datasets. This transparency allows for external validation and collaborative improvement.
- Closed Models: These are proprietary where the code and data are not publicly available.

2.1.5. Classification of Bottom-up Energy System Models

Another useful classification of energy models is the one provided by (Prina, 2020), proposing a re-elaborated classification scheme specifically tailored for bottom-up energy system models, as reported in Figure 2.3. This taxonomy begins with a distinction between analytical approaches, identifying top-down, hybrid, and bottom-up models. While top-down models focus on macroeconomic interactions and public welfare, the bottom-up approach allows for a better representation of specific technical components and their interconnections.

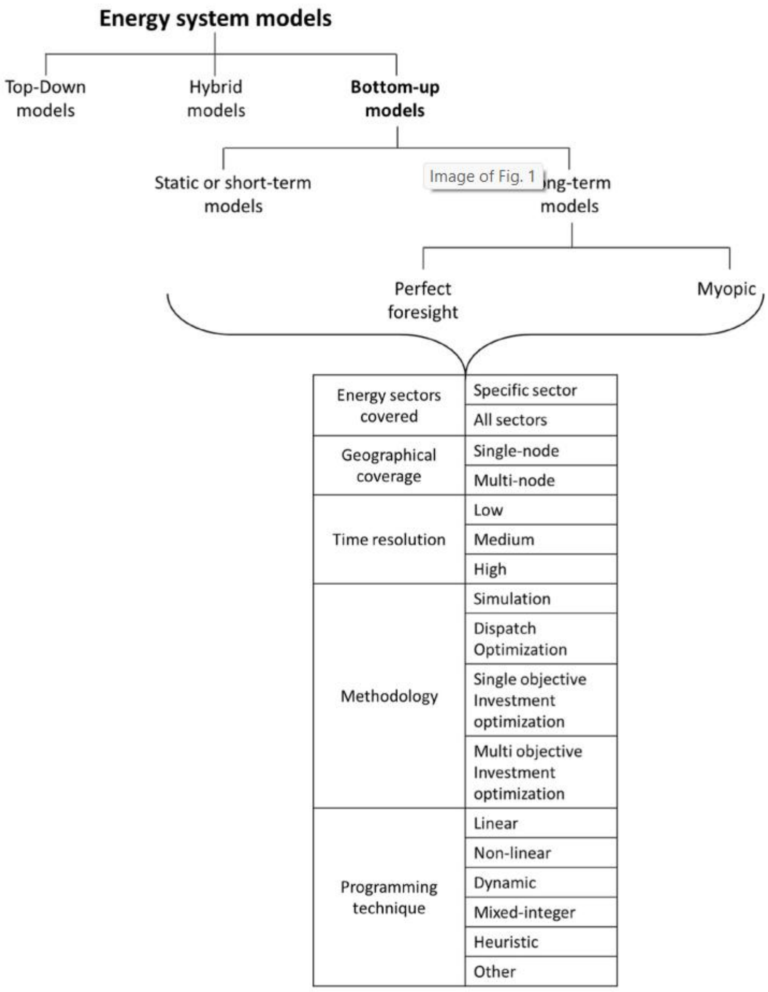

Figure 2.3: Bottom-Up Classification (Prina, 2020)

Within the bottom-up category, (Prina, 2020) establish a primary division based on the time horizon:

- Static or Short-term Models: These analyze the energy system configuration and future alternatives for a specific target year (e.g., 2030 or 2050),
- Long-term Models: These endogenously model the entire transition over several decades, accounting for variables such as technology life cycles, residual capacity, and commissioning/decommissioning schedules.

Long-term models are further categorized by their mathematical approach to the optimization problem:

- Perfect Foresight (Intertemporal): This assumes an omniscient decision-maker with full knowledge of the entire transition, including cost trends and performance projections, solving a unique optimization problem for all time periods simultaneously.

- Myopic (Recursive): This approach divides the horizon into a sequence of optimization sub-problems where the output of one period serves as the input for the next. While more realistic in reflecting real-world uncertainty, it can lead to sub-optimal decisions as the decider lacks complete information about the future.

Furthermore, bottom-up models can be classified according to the energy sector covered, the geographical coverage, the methodology, the programming technique and the time resolution, as already proposed by previous classification schemes.

A central and distinctive topic of the Prina et al. framework is the rigorous definition of temporal resolution, which is identified as a primary challenge in modern energy planning. As Variable Renewable Energy Sources (VRES) and storage become dominant, a low temporal resolution can lead to significant errors, such as underestimating VRES curtailments or overestimating the use of baseload plants.

To standardize this, the framework classifies temporal resolution based on the number of time-slices (stylized temporal representations of the simulation year) adopted:

- Low Resolution (Integral Method): Utilizes 1 to 32 time-slices. A common example is the 12 time-slice approach (4 seasons, 3 diurnal periods), which often presents a large generation mix error in high-renewable scenarios.
- Medium Resolution (Semi-dynamic Method): Incorporates 36 to 288 time-slices. This level typically employs representative days to increase accuracy while maintaining manageable computational costs.
- High Resolution (Dynamic Method): Corresponds to a full hourly time-step, represented by 8,760 time-slices. This approach captures the entire annual distribution of VRES variability.

In addition, (Prina, 2020) underline that the accuracy of an energy system model is primarily a function of its resolution (that can be low, medium and high) across four competing field, including not only time but also space, sector-coupling and techno-economic detail.

- Resolution in Space: Distinguishes between single-node (idealized transmission with no bottlenecks) and multi-node approaches. Higher spatial resolution is necessary to identify transmission constraints and the impact of geographically distributed generation.
- Resolution in Techno-Economic Detail: Evaluates the complexity of component modeling. Low resolution models consider power plants as fully flexible units with fixed efficiency. High resolution incorporates unit

commitment (UC) constraints such as ramp limits, time-dependent start-up costs, and part-load efficiency decay.

- Resolution in Sector-Coupling: Focuses on the synergies between energy sectors (electricity, heat, gas, transport, and industry). High resolution allows the model to exploit "Smart Energy System" (SES) synergies, which can increase overall efficiency and reduce costs.

(Prina, 2020) identify transparency as a critical secondary benchmark. They classify models into three levels:

- Low: "Black box" models with no public code or structured data.
- Medium: Models with complete documentation of mathematics and input databases.
- High: Open-source models that provide the full source code, ensuring the highest level of academic reproducibility.

Finally, on the paper 22 bottom-up energy models (13 bottom-up short-term and 9 bottom-up long-term energy models) are reviewed, classifying them according to resolution time, space, sector-coupling, techno-economic detail and transparency.

The classification and the comparative analysis provided by (Prina, 2020) have been used as one of the sources for the selection of the modelling tool in this thesis.

3 Selecting an Analytical Tool for the European Energy Transition

This chapter first defines the criteria used in this thesis to select an appropriate modelling tool for the analysis developed in the next chapters. The objective of this third chapter is to identify a model with the aim of developing a simple and linear optimization (LP) model capable of generating cost-optimal pathways to 2050 for an aggregated representation of Continental Europe, as discussed in the next chapters. Finally, the chapter compares different candidate tools and motivates the choice of OSeMOSYS as the most suitable framework.

3.1. Definition of Research Requirements and Functional Needs

To ensure the selection of a modelling tool that aligns with the objectives of the analysis deployed in the following chapters, a structured two-step approach is adopted, following the guidelines proposed in the report (Painuly, 2021).

Step 1: Research Question and Functional Requirements

The first phase of the selection process involves the definition of the "research question", which defines the broad category of models suitable for the analysis. For this study, the research question focuses on the implementation of an aggregated and simplified electrical model of continental Europe to analyze how power generation evolves across various scenarios and to test the validity of such simplified models in obtaining long-term trajectories and planning. These scenarios are defined by different projections of technology costs and performances, energy demands, CO_2 taxes, and strict emission constraints.

The study aims to identify the least-cost transition pathway, prioritizing the solution that is economically most efficient over the entire study period that extends until 2050. The model must therefore be capable of performing intertemporal optimization (Perfect Foresight), assuming a simultaneous decision-making process across the whole horizon to capture the transition trajectory rather than a static snapshot of a single target year.

Beyond the primary objective, several functional needs and secondary criteria have been identified, derived from the comparative properties of modelling tools as defined by the various classification frameworks previously examined in this study:

- Methodological Approach: The study requires a bottom-up model to analyze in detail the technical components and commodities.
- Analytical Function: The tool must perform capacity expansion (investment optimization) and planning to identify the most cost-effective evolution of the energy mix.
- Mathematical Logic: A Linear Programming (LP) approach is preferred to ensure transparency in the numerical results while maintaining a low computational cost, facilitating the execution of multiple scenarios.
- Spatial Scope: The model must support a single-region (single-node) representation, assuming an ideal transmission system without internal bottlenecks or losses to simplify the analysis of the continental system.
- Accessibility and Usability: The model must be open source, providing full access to its source code and underlying assumptions.
- Learning Resources: Given the thesis timeframe, a short learning curve is essential; the chosen tool must offer a robust support ecosystem, including user-friendly interfaces, comprehensive documentation, and high-quality learning materials such as tutorials and video courses.
- Scientific Validation: The tool must be widely recognized and extensively utilized within the academic/scientific community to ensure robustness and credibility of the findings.

Step 2: Model Review and Final Selection

The second step consists of consulting comprehensive publications and model reviews, such as those by (Hans-Kristian Ringkjob, 2018), (Prina, 2020) and many other published, to match the defined requirements with existing tools, balancing the need for intertemporal cost optimization with the requirement for computational efficiency and high transparency. This systematic process ensures that the selected tool is not only technically capable of identifying the best economic solution for the European power sector evolution but is also methodologically aligned with the research goals.

3.2. Review of Candidate Energy Modelling Tools

To identify the most suitable modelling tool for the objectives of this thesis, an extensive review of existing literature and established energy modelling frameworks was conducted. While several publications were consulted to understand the different available tools and their associated properties, the review by (Hans-Kristian Ringkjob, 2018) proved to be the most comprehensive and organic, providing a detailed analysis of 75 different modelling tools currently used in the energy and electricity sectors.

This work by (Hans-Kristian Ringkjob, 2018) served as the most organic starting point to map the capabilities of the different tools against the specific functional requirements of this research. Every model in that list was initially evaluated to determine if it met the core specifications: a bottom-up approach, support for Linear Programming (LP), open-source availability, and the capacity to model the power sector and CO_2 emissions.

From this initial screening, four primary candidates were extracted from the taxonomy as they satisfied the core specifications: Calliope, oemof, Balmorel, and OSeMOSYS.

Calliope

Calliope (Pfenninger P. , 2018), (Pfenninger, 2017), is an open-source energy system modeling framework originally developed at ETH Zurich. Designed as a bottom-up optimization tool, it is specifically engineered to be scale-agnostic, allowing researchers to investigate systems at any resolution, from individual urban districts to entire continents. Developed in Python, it formulates energy land-use and supply problems such as Linear Programming (LP) or Mixed-Integer Linear Programming (MILP) optimization problems via the Pyomo library. A fundamental aspect of its design is the strict separation between the modeling logic and the data: the framework's code remains constant, while the system is defined through human-readable YAML configuration files and CSV datasets.

The framework's versatility is mainly due to its modular "building-block" approach, where the physical system is represented through four primary top-level keys: technologies (defined by generic categories such as supply, demand, storage, transmission, and conversion), nodes (geographic or logical locations), carriers (commodities like electricity, heat, or hydrogen), and locations. Advanced modeling is supported through "Plus" technologies, such as Supply Plus (which incorporates primary resource storage before conversion) and Conversion Plus (handling complex n-m carrier conversion), allowing for sophisticated sector-coupling analysis.

Mathematically, Calliope's primary objective function is to minimize total system costs, accounting for a comprehensive range of economic variables including investment costs, fixed and variable O&M, fuel prices, and CO_2 caps or costs. The framework operates in three distinct modes: Planning mode for investment and capacity expansion planning with perfect foresight; Operational mode for economic dispatch using a receding horizon control algorithm to account for limited foresight; and the SPORES (Spatially explicit Practically Optimal RESults) method. This latter method is particularly relevant for policymaking, as it explores near-optimal alternatives within a predefined cost slack (typically 5-20%), identifying diverse system configurations that may be more socially or politically viable than the absolute cost-minimum solution.

Despite its analytical robustness, Calliope features specific limitations identified in its technical classification. While it excels in multi-area and multi-year operations, it typically operates on a one-year horizon scenario timeframe, lacking native support for multi-year investment (intertemporal) optimization. Furthermore, the framework presents a steep learning curve due to the complete absence of a Graphical User Interface (GUI).

Oemof

Oemof (Open Energy Modelling Framework) (S. Hilpert, 2018) is a modular, open-source framework developed by the Reiner Lemoine Institute in Germany, designed for favoring Open Science and collaborative development in energy system modeling. Developed in Python, it allows for the investigation of complex energy systems at various resolutions, ranging from local/community projects to global scenarios, by formulating them as Linear Programming (LP) or Mixed-Integer Linear Programming (MILP) problems using the Pyomo library. Oemof is characterized by a hybrid analytical approach, linking bottom-up technical detail with top-down systemic perspectives, making it suitable for forecasting, exploring, and back-casting scenarios. The framework's primary innovation is its graph-based architecture, where the energy system is represented as a directed graph. In this structure, Buses act as nodes that balance energy flows, while Components represent physical entities such as Sources (e.g., renewables), Sinks (e.g., demand), Storages, and Transformers (e.g., power plants, heat pumps). This logic supports sophisticated sector-coupling by integrating electricity, heating/cooling, and transport demands within a single model. Oemof is highly flexible regarding technology definitions, supporting different conversion types (1-1, n-1, 1-m, and n-m) and utilizing a transshipment grid model to analyze multi-area systems. Its objective function is centered on minimizing total system costs, which include investment costs, variable O&M, fuel prices, and specific CO_2 and emission costs. Notably, Oemof distinguishes itself from other frameworks by offering native support for GIS representation, facilitating the spatial analysis of topographic constraints. However, the framework is characterized by specific limitations that must be underlined:

- Timeframe and Investment Constraints: According to the technical classification, Oemof does not inherently support multi-year investment (intertemporal) or multi-year operation optimization in its standard configuration, typically focusing on a single-horizon scenario timeframe.

- Absence of a Graphical User Interface (GUI): Like Calliope, Oemof is entirely code-based. The lack of a dedicated GUI creates a steep learning curve, as users must possess advanced Python programming skills to build models, handle the library ecosystem (such as solph), and manage data workflows.
- Complexity in Setup: While its modularity is a strength, the requirement for users to manually define all components and connections within the graph-based logic requires a high level of expertise in energy system physics and mathematical optimization.

Balmorel

Balmorel (Frauke Wiese, 2018) is an open-source energy system model originally developed at the Technical University of Denmark (DTU) and implemented in the GAMS (General Algebraic Modeling System) programming language. It is characterized as a bottom-up, partial equilibrium model designed for the optimization of large-scale electricity and district heating sectors. Unlike many Python-based frameworks, Balmorel is specifically tailored for multi-regional and multi-country analysis. It was originally implemented for modeling the Nordic and Baltic energy markets. The model operates under the principle of perfect foresight, utilizing a mathematical approach based on Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) to achieve an integrated analysis of energy supply and demand.

The architectural strength of Balmorel lies in its ability to handle sector coupling, particularly the synergies between power and heat through technologies like combined heat and power (CHP) plants, heat pumps, and thermal storage. Its objective function is to maximise social welfare subject to technical, physical and regulatory constraints, which comprehensively include investment costs (capital expenditures), fixed and variable O&M, fuel prices, and CO_2 emission costs. A defining feature of Balmorel is its flexibility regarding model foresight. While it is primarily categorized as a perfect foresight model, where all future information is known to the optimizer, it can be configured in two distinct ways for long-term studies:

- Intertemporal Optimization: The model solves the entire planning horizon simultaneously with perfect foresight, allowing for the mathematically "true" optimal timing of investments.

- Recursive Dynamic (Myopic) Mode: The model solves one year at a time, moving forward with limited foresight (rolling horizon). This approach is often more realistic for simulating how markets and policies evolve.

This capability, combined with its support for multi-year investment and multi-year operation, allows Balmorel to determine the optimal sizing and trajectory of capacity additions over decades. Its grid representation follows a transshipment model, which efficiently handles energy transfers between nodes while considering interconnector capacities.

However, Balmorel presents several limitations that impact its accessibility and deployment:

- Software Dependency and Licensing: Being built in GAMS, the model requires GAMS installation. While the Balmorel code itself is open-source, solving large-scale MILP problems often requires commercial solvers (e.g., CPLEX, Gurobi) and a GAMS license, which can be a barrier compared to purely Python-based open-source tools.
- Absence of a Graphical User Interface (GUI): The framework is strictly code-based and data-driven via text and Excel files. The lack of a dedicated GUI creates a steep learning curve, requiring users to have high proficiency in GAMS syntax and data management.
- Technical Complexity: Due to its focus on large-scale international systems, the setup of its multi-area system and the management of its complex set of equations require significant expertise in both energy economics and mathematical optimization.

OSeMOSYS

OSeMOSYS (The Open-Source Energy Modeling System) (KTH-dESA, 2018) is a deterministic, linear optimization, long-term modeling framework designed to provide a transparent and modular tool for energy planning. It was developed through an extensive international collaboration involving the KTH Royal Institute of Technology, the International Atomic Energy Agency (IAEA), the United Nations Industrial Development Organization (UNIDO), Stanford University, University College London (UCL), the University of Cape Town (UCT), the Paul Scherrer Institute (PSI), the Stockholm Environment Institute (SEI), and North Carolina State University. Conceptually, OSeMOSYS computes the optimal energy supply mix, in terms of both generation capacity and energy delivery, to meet user-defined energy service demands for every year and time step of the study period. In its standard configuration, the model assumes a unique decision-maker, competitive markets, and perfect foresight, aiming to minimize the total discounted system costs. Its scope is highly flexible, allowing for the integrated analysis of individual or multiple sectors, including heat, electricity, and transport, across user-defined spatial and temporal domains.

In mathematical terms, the framework primarily utilizes Linear Programming (LP), although Mixed-Integer Linear Programming (MILP) is frequently applied for specific functions, such as the optimization of discrete power plant capacity expansions. A defining characteristic of OSeMOSYS is its broad and flexible definition of "technology" and "energy vector." Technology in this context represents any asset within the energy conversion chain, from resource extraction and secondary processing, to transmission, distribution, and end-use appliances (e.g., oil refineries, hydropower plants, or domestic heating systems). Each technology is defined by a transfer function governed by a wide array of techno-economic and environmental parameters, including investment and O&M costs, efficiency, availability, emission factors etc.… These technologies draw on a set of resources defined by specific potential and costs, while policy scenarios can be used to impose technical constraints or environmental targets.

The original source code of OSeMOSYS is written in GNU MathProg, a high-level mathematical programming language. Despite its power, the code is remarkably concise, consisting of approximately 700 lines in its full version, and is structured to be like algebraic expressions, making it accessible to both experts and non-experts. However, parallel versions of the code have been developed in GAMS and Python. The model typically employs the open-source GLPK (GNU Linear Programming Kit) solver to translate the code into matrices and find the optimal numerical solution.

While OSeMOSYS applications can be executed via a command-line interface, a robust ecosystem of User Interfaces (GUIs) has been developed to facilitate teaching, capacity building, and complex data management:

- MoManI (Model Management Infrastructure) (Mark Howells M. P., 2017): A free, open-source interface (available in both online and desktop versions) used for creating models, managing large datasets, and visualizing results.
- ClicKSand (Cannone, 2024): An Excel-based interface that simplifies the population of data templates, effectively bridging the gap between spreadsheet data entry and the model's algebraic requirements.
- MUIO (Model User Interface for OSeMOSYS) (MUIO, 2024) : A dedicated tool designed to streamline the interaction between the user and the solver, simplifying scenario management.

Through the integration of these tools and its open-source "building-block" logic, as demonstrated in the OSeMOSYS Global initiative, the framework provides a powerful, transparent alternative to proprietary modeling systems.

3.3. Rationale for Selecting OSeMOSYS

To identify the most suitable framework for this research, a screening process was conducted starting from an initial list of 75 energy models (Hans-Kristian Ringkjob, 2018). The screening process focuses then to four primary candidates, Calliope, oemof, Balmorel, and OSeMOSYS, which represented the best fit between technical requirements and model accessibility. However, to effectively identify a least-cost transition pathway, the chosen tool must be capable of performing intertemporal optimization under the assumption of perfect foresight. This requirement is fundamental for capturing a dynamic transition trajectory across the entire analysis period, rather than providing static snapshots of independent target years.

The focus was further refined to Balmorel and OSeMOSYS by applying Prina's taxonomy (Prina, 2020), which classifies bottom-up energy system models based on their methodology and time horizon. According to this classification, both Balmorel and OSeMOSYS are categorized as bottom-up long-term models, distinguishing them from frameworks like Calliope and oemof, defined as short-term models, because they analyse the energy system in a single target year (e.g., 2030 or 2050) and assess system configurations and alternatives for that specific year, without endogenously modelling the full transition pathway year by year over the entire modelling period. By optimizing the decision-making process simultaneously across the whole temporal horizon, Balmorel and OSeMOSYS ensure that investment pathways are mathematically consistent with long-term decarbonization targets and can represent the evolution towards the target year by accounting for dynamics such as remaining capacity, decommissioning and new installations, and technology lifetimes.

Between these two final candidates, OSeMOSYS was ultimately selected due to a series of different technical and economic advantages. While Balmorel is a robust tool, its implementation in GAMS often necessitates proprietary licensing and expensive commercial solvers for large-scale applications. In contrast, OSeMOSYS is built on a fully open-source philosophy; by utilizing GNU MathProg or Python and open-source solvers like GLPK, it requires no upfront financial investment, ensuring total transparency and reproducibility in line with open-science standards.

Furthermore, OSeMOSYS was favored for its significantly lower learning curve and supporting materials available. The framework is supported by different user interfaces, including MoManI, ClicKSand, and MUIO. This accessibility is increased by a comprehensive library of documentation, video courses, and tutorials, which are designed to be more immediately understandable for academic users.

From a modeling perspective, OSeMOSYS's objective function is explicitly designed to minimize total discounted costs, which aligns directly with this study's goal of identifying a least-cost transition pathway. In contrast, Balmorel is a partial equilibrium model that typically aims to maximize social welfare, a broader objective that can introduce additional layers of complexity. Finally, the proven track record of OSeMOSYS in large-scale international applications and its extensive use in master's and doctoral theses worldwide provide a validated foundation for its application in this research, as reported in (Plazas-Niño F. , 2025) and (CCG, 2025).

Among all the available OSeMOSYS User Interfaces, MUIO (5.3 Version) was selected for this research, largely due to the comprehensive video lessons and technical support materials offered by the Climate Compatible Growth (CCG) programme (Climate Compatible Growth, 2025). Funded by the UK's Foreign, Commonwealth and Development Office (FCDO), the CCG initiative represents a strategic collaboration between leading institutions, including Loughborough University, Imperial College London, the University of Oxford, KTH Royal Institute of Technology, the Centre for Global Equality, the University of Cambridge, Sustain 2030, Climate Parliament, and The Open University. This extensive educational framework provided a reliable and well-documented pathway for the model's implementation, ensuring a robust learning process through high-quality academic resources.

3.4. OSeMOSYS

This section provides a detailed description of the OSeMOSYS (Open-Source Energy Modelling System) framework. To understand how the model optimizes energy systems, it is essential to break it down into its constituent parts: the structural dimensions (Sets), the numerical data required (Parameters/Inputs), the results generated (Variables/Outputs), and the mathematical equations governing the system (Equations). Finally, the overarching operational logic is explained. The OSeMOSYS model analysis presented here is specifically tailored to the inputs and characteristics of the selected MUIO interface. Additional information regarding the main OSeMOSYS equations, as the algebraic formulations, are reported in Appendix A.

3.4.1. Introduction to OSeMOSYS

The Open-Source Energy Modelling System (OSeMOSYS) (Mark Howells H. R., 2011), (KTH-dESA, 2018), is a deterministic, linear optimization, long-term modeling framework specifically designed to inform the development of local, national, and multi-regional energy strategies.

OSeMOSYS computes the optimal energy supply mix, both in terms of generation capacity and energy delivery, required to meet energy service demands across a user-defined spatial and temporal domain. By minimizing the total discounted system costs, the model identifies the most efficient pathways for energy transition while accounting for the techno-economic characteristics of a wide range of technologies.

A defining feature of OSeMOSYS is its flexible and comprehensive definition of "technology" and "energy vector." Technology is treated as any asset operating within an energy conversion process, spanning the entire value chain from resource extraction and processing to transmission, distribution, and end-use appliances, such as oil refineries, hydropower plants, or heating systems. Each technology is defined by a transfer function governed by numerous parameters, including investment and operating costs, efficiency, availability, and emission factors.

Mathematically, while primarily utilizing Linear Programming (LP), the framework can incorporate Mixed-Integer Linear Programming (MILP) to handle discrete variables, such as specific power plant capacity expansions. In its standard configuration, the model assumes a unique decision-maker with perfect foresight, operating within competitive markets. Developed to be highly accessible, the original code is written in GNU MathProg, consisting of approximately 700 lines of algebraic expressions, though parallel versions exist in Python and GAMS to support diverse user communities. By using open-source solvers like GLPK, OSeMOSYS translates complex energy systems into solvable matrices, providing a transparent and modular tool for capacity building and strategic policy analysis.

3.4.2. Model Structure: Sets

In the OSeMOSYS framework, *Sets* constitute the foundational architecture of the model, remaining invariant across different scenarios. They define the structural boundaries of the system, including the spatial scope (Regions), the temporal discretization (Years and Time Slices), and the technological portfolio. Furthermore, Sets categorize the energy vectors (Fuels) and environmental impacts (Emissions) to be analyzed. The sets of OSeMOSYS, with their indexes (), are presented below, sourced in (KTH-dESA, 2018):

- Year (y): It represents the time horizon of the model; it contains all the years to be considered in the analysis.
- Timeslice (l): The temporal resolution of the system is managed through 'time slices,' which represent fractions of the year used to distinguish between high and low demand periods. This is particularly vital for non-storable energy sources. To minimize processing time, these slices are usually grouped into a multi-level hierarchy, typically comprising seasons, day types, and day/night divisions, ensuring that the model captures essential variability without becoming computationally prohibitive.
- Season (ls): This set is used to discretize the year into distinct seasonal periods. The order of these values establishes the chronological sequence of these periods within the modelled year.
- Day Types (ld): This set allows for the representation of intra-seasonal variability by partitioning the season into representative day types. The order of these values establishes the chronological sequence of these periods within the relative season.
- Daily Time Bracket (lh): This set subdivides a representative day into discrete segments. The order of these values establishes the chronological sequence of these periods within the relative day.
- Region (r): It sets the regions to be modelled.
- Technology (t): It includes any element of the energy system that changes a commodity from one form to another, uses it or supplies it. All system components are set up as a ‘technology’ in OSeMOSYS.
- Storage (s): It includes storage facilities in the model.
- Fuel (f): It includes any energy vector, energy service or proxies entering or exiting technologies.
- Emission (e): It includes any kind of emission potentially deriving from the operation of defined technologies.
- Mode of operation (m): It defines the number of modes of operation that the technologies can have. If a technology can have various input or output fuels and it can choose the mix of these input or output fuels.

Timeslices

To capture the intra-annual dynamics of energy supply and demand, OSeMOSYS utilizes a temporal discretization structure by defining Time Slices. Instead of modeling every hour of the year, which would significantly increase the computational burden and solving time, the model aggregates hours into representative temporal brackets. These Time Slices are defined hierarchically as the product of three main dimensions: the number of Seasons, the number of Day Types, and the number of Daily Time Brackets.

$$\mathrm{N.\,of\,Timeslices} = \mathrm{N.\,of\,Seasons} * \mathrm{N.\,of\,Day\,Types} * \mathrm{N.\,of\,Daily\,Time\,Brackets}$$

This granular resolution is essential for accurately representing the energy system's flexibility requirements; it allows the model to align the fluctuating availability of Variable Renewable Energy (VRE), such as solar and wind, with the specific timing of energy demand. Consequently, Time Slices provide the necessary technical details to evaluate capacity requirements, storage needs, and system reliability while maintaining the model's computational tractability.

3.4.3. Input Data: Parameters

Parameters represent the exogenous numerical inputs provided by the user to the model. While the underlying structural framework, determined by the Sets, typically remains invariant across different simulations, modifying specific parameter values is fundamental for developing and running different scenarios and conducting sensitivity analyses. From a technical perspective, each parameter is indexed over one or more sets, indicating that the parameter is function of that set. A list and brief description of the parameters is given below, sourced in (KTH-dESA, 2018).

Global parameter

- YearSplit [l,y]: This parameter is used to set the duration of each time slice (sub-annual time increment of the model). It is a time-dependent parameter and is specified as a fraction of the total year for each time-slice in each year (i.e. it will have a value between 0 and 1). The summation of the Year Split over one year should be equal to 1 (except for small rounding errors).
- DaySplit [lh,y]: This parameter is used to set the duration of one DailyTimeBracket in one specific day as a fraction of the year. It is a time-dependent parameter and is specified as a fraction of the total year for each time-slice in each year (i.e. it will have a value between 0 and 1).
- DaysInDayType [ls,ld,y]: This parameter is used to specify the number of sequential days in a single occurrence of a day type. It is specified for each daytype in each season. It is a natural number, ranging from 1 to 7.
- DiscountRate [r]: Region specific value for the discount rate, expressed in decimals.

- Conversionls [l,ls]: Binary parameter linking one TimeSlice to a certain Season. It has value 0 if the TimeSlice does not pertain to the specific season, 1 if it does.
- Conversionld [ld,l]: Binary parameter linking one TimeSlice to a certain DayType. It has value 0 if the TimeSlice does not pertain to the specific DayType, 1 if it does.
- Conversionlh [lh,l]: Binary parameter linking one TimeSlice to a certain DaylyTimeBracket. It has value 0 if the TimeSlice does not pertain to the specific DaylyTimeBracket, 1 if it does.
- DepreciationMethod[r]: Binary parameter defining the type of depreciation to be applied. It has value 1 for sinking fund depreciation, value 2 for straight-line depreciation. Generally, the sinking fund depreciation is applied.

Demands

- SpecifiedAnnualDemand [r,f,y]: Total specified fuel demand for the year.
- SpecifiedDemandProfiles [r,f,l,y]: Annual fraction of energy-service or commodity demand that is required in each time slice. For each year, all the defined SpecifiedDemandProfile input values should sum up to 1.
- AccumulatedAnnualDemand [r,f,y]: Accumulated Demand for a certain commodity in one specific year. It cannot be defined for a commodity if its SpecifiedAnnualDemand for the same year is already defined and vice versa.

SpecifiedAnnualDemand is used when the demand follows a specific intra-annual distribution, defined through a demand profile, requiring the model to balance supply and demand within each individual time slice (e.g., meeting hourly electricity loads). In contrast, AccumulatedAnnualDemand is used for commodities where only the total yearly consumption is relevant, allowing the model the flexibility to satisfy the requirement at any point during the year without a predefined seasonal or daily pattern.

Performance

- CapacityToActivityUnit[r,t]: Conversion factor linking the energy that would be produced when one unit of capacity is fully used in one year.
- CapacityFactor[r,t,l,y]: Capacity available per each TimeSlice expressed as a fraction of the total installed capacity, with values ranging from 0 to 1.
- AvailabilityFactor[r,t,y]: Maximum time a technology can run in the whole year, as a fraction of the year ranging from 0 to 1. This parameter account for planned outages.

- OperationalLife[r,t]: Useful lifetime of a technology, expressed in years.
- ResidualCapacity[r,t,y]: Installed capacity available from before the modelling period.
- InputActivityRatio[r,t,f,m,y]: Rate of use of a commodity by a technology, as a ratio of the rate of activity.
- OutputActivityRatio[r,t,f,m,y]: Rate of commodity output from a technology, as a ratio of the rate of activity.

Technology cost

- CapitalCost[r,t,y]: Capital investment cost of a technology, per unit of capacity.
- VariableCost[r,t,m,y]: Variable O&M cost of a technology for a given mode of operation , per unit of activity.
- FixedCost[r,t,y]: Fixed O&M cost of a technology, per unit of capacity.

Storage

In OSeMOSYS, energy storage is represented through a decoupled structure consisting of a storage reservoir to manage energy capacity and separate power technologies that act as charging and discharging interfaces. This distinction allows the model to independently optimize the instantaneous rate of energy flow versus the total volume of energy stored, accurately reflecting the technical and economic limits of different storage assets.

- TechnologyToStorage[r,t,s,m]: Binary parameter linking the power technology to the storage facility it charges. It has value 1 if the technology and the storage facility are linked, 0 otherwise.
- TechnologyFromStorage[r,t,s,m]: Binary parameter linking a storage facility to the power technology it feeds. It has value 1 if the technology and the storage facility are linked, 0 otherwise.
- StorageLevelStart[r,s]: Level of storage at the beginning of first modelled year, in units of activity.
- StorageMaxChargeRate[r,s]: Maximum charging rate for the storage, in units of activity per year.
- StorageMaxDischargeRate[r,s]: Maximum discharging rate for the storage, in units of activity per year.
- MinStorageCharge[r,s,y]: It is lower bound to the amount of energy stored, as a fraction of the maximum, with a number ranging between 0 and 1. The storage technology cannot be emptied below this level.
- OperationalLifeStorage[r,s]: Useful lifetime of the storage facility.
- CapitalCostStorage[r,s,y]: Investment costs of storage additions, defined per unit of storage capacity.

- ResidualStorageCapacity[r,s,y]: Installed storage capacity available from before the modelling period.

Capacity Constraints

- CapacityOfOneTechnologyUnit[r,t,y]: Capacity of one new unit of a technology. In case this parameter is added, the related technology will be installed only in batches of the specified capacity, and the problem will turn into a Mixed Integer Linear Problem.
- TotalAnnualMaxCapacity[r,t,y]: Total maximum existing (residual plus cumulatively installed) capacity allowed for a technology in a specified year.
- TotalAnnualMinCapacity[r,t,y]: Total minimum existing (residual plus cumulatively installed) capacity allowed for a technology in a specified year.
- TotalAnnualMaxCapacityInvestment[r,t,y]: Maximum capacity investment of a technology, expressed in power units.
- TotalAnnualMinCapacityInvestment[r,t,y]: Minimum capacity investment of a technology, expressed in power units.

Activity Constraints

- TotalTechnologyAnnualActivityUpperLimit[r,t,y]: Total maximum level of activity allowed for a technology in one year.
- TotalTechnologyAnnualActivityLowerLimit[r,t,y]: Total minimum level of activity allowed for a technology in one year.
- TotalTechnologyModelPeriodActivityUpperLimit[r,t]: Total maximum level of activity allowed for a technology in the entire modelled period.
- TotalTechnologyModelPeriodActivityLowerLimit[r,t]: Total minimum level of activity allowed for a technology in the entire modelled period.

Emissions

- EmissionActivityRatio[r,t,e,m,y]: Emission factor of a technology per unit of activity, per mode of operation.
- EmissionsPenalty[r,e,y]: Penalty per unit of emission.
- AnnualExogenousEmission[r,e,y]: It accounts for additional annual emissions, on top of those computed endogenously by the model.
- AnnualEmissionLimit[r,e,y]: Annual upper limit for a specific emission generated in the whole modelled region.
- ModelPeriodEmissionLimit[r,e]: Annual upper limit for a specific emission generated in the whole modelled region, over the entire modelled period.

3.4.4. Model Outputs: Variables

Variables represent the endogenous outputs determined by the optimization solver during the simulation. Like parameters, variables are mathematically indexed over one or more Sets, which defines their spatial and temporal resolution within the model.

To facilitate the convergence of the optimization algorithm and reduce the complexity of the solution space, non-negativity constraints are imposed on most of these variables. This ensures that physical quantities, such as installed capacity, energy generation, or resource consumption, remain within logically and physically consistent bounds (i.e., they cannot be less than zero). A list and brief description of the parameters is given below, sourced in (KTH-dESA, 2018).

Demands

- RateOfDemand[r,l,f,y]>=0: Intermediate variable. It represents the energy that would be demanded for each fuel in one time slice l if the latter lasted the whole year. It is a function of the parameters SpecifiedAnnualDemand and SpecifiedDemandProfile.
- Demand[r,l,f,y]>=0: Demand for one fuel in one time slice.

Storage

- RateOfStorageCharge[r,s,ls,ld,lh,y]: Intermediate variable. It represents the commodity that would be charged to the storage facility s in one time slice if the latter lasted the whole year. It is a function of the RateOfActivity and the parameter TechnologyToStorage.
- RateOfStorageDischarge[r,s,ls,ld,lh,y]: Intermediate variable. It represents the commodity that would be discharged from storage facility s in one time slice if the latter lasted the whole year. It is a function of the RateOfActivity and the parameter TechnologyFromStorage.
- NetChargeWithinYear[r,s,ls,ld,lh,y]: Net quantity of commodity charged to storage facility s in year y. It is a function of the RateOfStorageCharge and the RateOfStorageDischarge and it can be negative.
- NetChargeWithinDay[r,s,ls,ld,lh,y]: Net quantity of commodity charged to storage facility s in daytype ld. It is a function of the RateOfStorageCharge and the RateOfStorageDischarge and can be negative.
- StorageLevelYearStart[r,s,y]>=0: Level of stored commodity in storage facility s in the first time step of year y.
- StorageLevelYearFinish[r,s,y]>=0: Level of stored commodity in storage facility s in the last time step of year y.

- StorageLevelSeasonStart[r,s,ls,y]>=0: Level of stored commodity in storage facility s in the first time step of season ls.
- StorageLevelSeasonFinish[r,s,ls,y]>=0: Level of stored commodity in storage facility s in the last time step of season ls.
- StorageLevelDayTypeStart[r,s,ls,ld,y]>=0: Level of stored commodity in storage facility s in the first time step of daytype ld.
- StorageLevelDayTypeFinish[r,s,ls,ld,y]>=0: Level of stored commodity in storage facility s in the last time step of daytype ld.
- StorageLowerLimit[r,s,y]>=0: Minimum allowed level of stored commodity in storage facility s, as a function of the storage capacity and the user-defined MinStorageCharge ratio.
- StorageUpperLimit[r,s,y]>=0: Maximum allowed level of stored commodity in storage facility s. It is the total existing capacity of storage facility s and it is obtained as the sum of newly installed and pre-existing capacities.
- AccumulatedNewStorageCapacity[r,s,y]>=0: Cumulative capacity of newly installed storage from the beginning of the time domain to year y.
- NewStorageCapacity[r,s,y]>=0: Capacity of newly installed storage in year y.
- CapitalInvestmentStorage[r,s,y]>=0: Undiscounted investment in new capacity for storage facility s. Derived from the NewStorageCapacity and the parameter CapitalCostStorage.
- DiscountedCapitalInvestmentStorage[r,s,y]>=0: Investment in new capacity for storage facility s, discounted through the parameter DiscountRate.
- SalvageValueStorage[r,s,y]>=0: Salvage value of storage facility s in year y, as a function of the parameters OperationalLifeStorage and DepreciationMethod[r].
- DiscountedSalvageValueStorage[r,s,y]>=0: Salvage value of storage facility s, discounted through the parameter DiscountRate.
- TotalDiscountedStorageCost[r,s,y]>=0: Difference between the discounted capital investment in new storage facilities and the salvage value in year y.

Capacity Variables

- NumberOfNewTechnologyUnits[r,t,y]>=0, integer: Number of newly installed units of technology t in year y, as a function of the parameter CapacityOfOneTechnologyUnit.
- NewCapacity[r,t,y]>=0: Newly installed capacity of technology t in year y.
- AccumulatedNewCapacity[r,t,y]>=0: Cumulative newly installed capacity of technology t from the beginning of the period to year y.
- TotalCapacityAnnual[r,t,y]>=0: Total existing capacity of technology t in year y (sum of cumulative newly installed and residual capacity).

Activity Variables

- RateOfActivity[r,l,t,m,y] >=0: Intermediate variable. It represents the activity of technology t in one mode of operation and in time slice l, if the latter lasted the whole year.
- RateOfTotalActivity[r,t,l,y] >=0: Sum of the RateOfActivity of a technology over the modes of operation.
- TotalTechnologyAnnualActivity[r,t,y] >=0: Total annual activity of technology t.
- TotalAnnualTechnologyActivityByMode[r,t,m,y]>=0: Annual activity for technology t in mode of operation m.
- TotalTechnologyModelPeriodActivity[r,t]: Sum of the TotalTechnologyAnnualActivity over the years of the modelled period.
- RateOfProductionByTechnologyByMode[r,l,t,m,f,y] >=0: Intermediate variable. It represents the quantity of fuel f that technology t would produce in one mode of operation and in time slice l, if the latter lasted the whole year. It is a function of the variable RateOfActivity and the parameter OutputActivityRatio.
- RateOfProductionByTechnology[r,l,t,f,y]>=0: Sum of the RateOfProductionByTechnologyByMode over the modes of operation.
- ProductionByTechnology[r,l,t,f,y] >=0: Production of fuel f by technology t in time slice l.
- ProductionByTechnologyAnnual[r,t,f,y] >=0: Annual production of fuel f by technology t.
- RateOfProduction[r,l,f,y] >=0: Sum of the RateOfProductionByTechnology for that fuel f over all the technologies.
- Production[r,l,f,y] >=0: Total production of fuel f in time slice l. It is the sum of the ProductionByTechnology over all technologies.
- RateOfUseByTechnologyByMode[r,l,t,m,f,y]>=0: Intermediate variable. It represents the quantity of fuel f that technology t would use in one mode of operation and in time slice l, if the latter lasted the whole year. It is the function of the variable RateOfActivity and the parameter InputActivityRatio.
- RateOfUseByTechnology[r,l,t,f,y]>=0: Sum of the RateOfUseByTechnologyByMode over the modes of operation.
- UseByTechnologyAnnual[r,t,f,y] >=0: Annual use of fuel f by technology t.
- UseByTechnology[r,l,t,f,y] >=0: Use of fuel f by technology t in time slice l.
- Use[r,l,f,y] >=0: Total use of fuel f in time slice l. It is the sum of the UseByTechnology over all technologies.
- Trade[r,rr,l,f,y]: Quantity of fuel f traded between region r and rr in time slice l.

- TradeAnnual[r,rr,f,y]: Annual quantity of fuel f traded between region r and rr. It is the sum of the variable Trade over all the time slices.
- ProductionAnnual[r,f,y] >=0: Total annual production of fuel f. It is computed as the sum of the variable Production over all technologies.
- UseAnnual[r,f,y] >=0: Total annual use of fuel f. It is the sum of the variable Use over all technologies.

Costing Variables

- CapitalInvestment[r,t,y] >=0: Undiscounted cost of investment in new capacity of technology t. It is a function of the NewCapacity and the parameter CapitalCost.
- DiscountedCapitalInvestment[r,t,y] >=0: Investment in new capacity of technology t, discounted through the parameter DiscountRate.
- SalvageValue[r,t,y] >=0: Salvage value of technology t in year y, as a function of the parameters OperationalLife and DepreciationMethod. The Salvage Value represents the residual economic value of a technology at the end of the modelling horizon, accounting for the remaining operational life of assets that have not yet reached their full decommissioning age. In OSeMOSYS, this value is subtracted from the objective function to ensure that investments made late in the simulation period are not unfairly penalized by the finite nature of the study's timeframe.
- DiscountedSalvageValue[r,t,y] >=0: Salvage value of technology t, discounted through the parameter DiscountRate.
- OperatingCost[r,t,y] >=0: Undiscounted sum of the annual variable and fixed operating costs of technology t.
- DiscountedOperatingCost[r,t,y] >=0: Annual OperatingCost of technology t, discounted through the parameter DiscountRate.
- AnnualVariableOperatingCost[r,t,y] >=0: Annual variable operating cost of technology t. Derived from the TotalAnnualTechnologyActivityByMode and the parameter VariableCost.
- AnnualFixedOperatingCost[r,t,y] >=0: Annual fixed operating cost of technology t. Derived from the TotalCapacityAnnual and the parameter FixedCost.
- TotalDiscountedCostByTechnology[r,t,y] >=0: Difference between the sum of discounted operating cost, capital cost, emission penalties and the salvage value, for technology t.
- TotalDiscountedCost[r,y] >=0: Sum of the TotalDiscountedCostByTechnology over all the technologies.

Emissions

- AnnualTechnologyEmissionByMode[r,t,e,m,y] >=0: Annual emission of agent e by technology t in mode of operation m. Derived from the RateOfActivity and the parameter EmissionActivityRatio.
- AnnualTechnologyEmission[r,t,e,y]>=0: Sum of the AnnualTechnologyEmissionByMode over the modes of operation.
- AnnualTechnologyEmissionPenaltyByEmission[r,t,e,y] >=0: Undiscounted annual cost of emission e by technology t. It is a function of the AnnualTechnologyEmission and the parameter EmissionPenalty.
- AnnualTechnologyEmissionsPenalty[r,t,y] >=0: Total undiscounted annual cost of all emissions generated by technology t. Sum of the AnnualTechnologyEmissionPenaltyByEmission over all the emitted agents.
- DiscountedTechnologyEmissionsPenalty[r,t,y] >=0: Annual cost of emissions by technology t, discounted through the DiscountRate.
- AnnualEmissions[r,e,y] >=0: Sum of the AnnualTechnologyEmission over all technologies.
- ModelPeriodEmissions[r,e] >=0: Total system emissions of agent e in the model period, accounting for the emissions by technologies.

3.4.5. Mathematical Formulation: Equations

The OSeMOSYS code is organized into discrete functional blocks of equations, which collectively comprise a single objective function and a comprehensive set of equations. This modular architecture is a defining feature of the framework, allowing for a high degree of flexibility; users can easily integrate or omit specific code modules according to the specific scope of their research. The following section provides a narrative overview of the model's main equations; further details regarding their algebraic formulation are provided in Appendix A, sourced in (Mark Howells H. R., 2011).

Objective Function

The objective function of the model is to minimize the Total Discounted System Cost (Z) (over the entire modelling period), that aggregates all expenditures across the modelled regions (r) and years (y). Mathematically, the function is defined as:

$$\min Z = \sum\nolimits_{y,r} \mathrm{TotalDiscountedCost}_{y,r} \quad (3.1)$$

According to the model's cost accounting logic, the Total Discounted Cost is the sum of Total Discounted Cost by Technology and Total Discount Storage Cost.

Total Discount Cost by Technology is obtained from the following components, summed for each year, technology and region and then discounted back to the first year modelled:

- Operating Costs: including both fixed costs and variable costs. The variable cost for each technology is calculated for each time slices as the product of the rate of activity and the unit operating cost. This cost is calculated for each time slices during the year and then summed to determine an annual variable operating cost per each technology. The annual fixed operating cost per each technology is calculated by multiplying the total installed capacity of a technology per a unit fixed cost. The total annual operating cost per each technology is the sum of the fixed and variable cost and is then discounted back to the first year modelled. This is done using a global discounted rate applied to the middle of the year in which the costs are considered.
- Capital Investment: The upfront costs associated with New Capacity installations. New capacity is assumed to be commissioned and available at the beginning of the year and the capital cost are determined by the level of new capacity per each technology invested multiplied by a per unit capital cost. This cost is then discounted back to the first year modelled, using a global discount rate applied to the beginning of the year in which the technology is invested.
- Technology Emissions Penalty: The economic cost imposed on carbon-intensive activities to drive decarbonization, due to emission penalty. This is achieved by multiplying the annual emissions for each technology with the per unit emissions penalty. Summing the penalty for each emissions gives the total emissions related penalty associated with the use of a given technology for each year. This cost is then discounted back to the first year. This is done using a global discounted rate applied to the middle of the year in which the costs are considered.
- Salvage Value (subtracted): This represents the residual economic value of assets that remain operational beyond the end horizon, ensuring that long-lived investments are not penalized by the model's end-date. When a technology is invested during the model period but ends its operational life within the horizon, it is assumed to have no value, but if that technology still has some operational life at the end of the period it has a remaining value. The remaining value is the salvage value and is determined in the model assuming depreciation. In OSeMOSYS, the calculation of the Salvage Value follows two primary methodologies, governed by the DepreciationMethod parameter:
    - Linear Depreciation (Method 2): This method is applied when the DepreciationMethod parameter is set to 2 (or if the discount rate is

zero). In this case, the asset's value decreases at a constant rate over time, reflecting a straightforward proportional reduction. In the MUIO (Version 5.3) interface, the straight-line method is used by default for salvage value calculations, even when a discount rate >0 is applied.

- Sinking Fund Depreciation (Method 1): This method is applied when the DepreciationMethod is set to 1 and the DiscountRate is positive. Unlike the linear approach, the Sinking Fund method accounts for the time value of money. This results in a non-linear depreciation curve that is typically less aggressive in the early years of the asset's life, more accurately reflecting financial annuities and interest-bearing capital.

Then the Salvage Value is discounted to the first model year by a discount rate applied over the modelling period.

Total Discounted Storage Cost is obtained from the following components, summed for each year, storage and region and then discounted back to the first year modelled:

- Capital Investment Storage: The upfront costs associated with New Storage Capacity installations. New Storage capacity is assumed to be commissioned and available at the beginning of the year in which the storage is invested and the capital storage cost are determined by the level of new Storage capacity invested multiplied by a per unit capital cost. That cost is then discounted back to the first year modelled, using a global discount rate applied to the beginning of the year in which the storage is invested.
- Salvage Value of Storage (subtracted): This represents the residual economic value of storage assets that remain operational beyond the end horizon, ensuring that long-lived storage investments are not penalized by the model's end-date. In OSeMOSYS, the calculation of the Salvage Value of Storage follows two primary methodologies, governed by the DepreciationMethod parameter, as previously described. Then the Salvage Value of Storage is discounted back to the first model year by a discount rate applied over the modelling period.

Rate Of Demand

OSeMOSYS translates total annual energy requirements of each fuel f into a time-dependent variable known as the RateOfDemand. This variable represents the instantaneous power demand for a specific fuel within each TimeSlice.

$$\mathrm{RateOfDemand}[r,l,f,y] = \frac{\mathrm{SpecifiedAnnualDemand}[r,f,y] * \mathrm{SpecifiedDemandProfile}[r,f,l,y]}{\mathrm{YearSplit}[l,y]} \quad (3.2)$$

From a computational and optimization perspective, the RateOfDemand is used as the primary active constraint (or binding constraint) within the optimization process. In a cost-minimization framework, if no demand were specified, the solver would reach a trivial solution of zero (zero investment, zero activity, and zero cost). The RateOfDemand acts as the fundamental "forcing factor" that defines the minimum threshold the system must satisfy. By imposing this requirement within the Energy Balance equations, it impose the model to activate the technology chain, triggering investments in NewCapacity and incurring OperatingCosts due to the technology RateOfActivity, ensuring that the supply matches this rate in every time slice.

Capacity Adequacy A & B

There must be enough capacity of a particular technology to meet its energy production requirements in each time slice (Capacity Adequacy A) and annually (Capacity Adequacy B).

- Capacity Adequacy 'A': In every time-slice the total available capacity of each technology must be sufficient to satisfy and meet the activity requirement. Their total de-rated capacity has to be larger than their rate of activity during any time slices. The available capacity each time slices is the Total Capacity, defined as the sum of the residual capacity and accumulated new capacity minus capacity retirements. The sum is then derated by the capacity factor, to determine the total de-rated capacity for that time slices.
- Capacity Adequacy 'B': Ensures that each technology has an available capacity sufficient to account for their annual production activity. The annual production, that is the sum of their production in each time slice, has to be less than their total de-rated available capacity multiplied by the Availability Factor.

Energy Balance A & B

In the OSeMOSYS framework, the equilibrium of the energy system is maintained through specific constraints known as Energy Balances. These equations ensure that for every fuel, in every region and year, the supply provided by technologies is sufficient to meet the demand and internal consumption/use by other technologies.

- Energy Balance 'A': focuses on time slices, ensuring that the total fuel production for each technology in each time slices is higher or at least equal than the sum of demand and overall use by other technologies of each fuel in that time slice.

- Energy Balance 'B': ensures that for each year the total annual production for each fuel is higher or at least equal than the sum of the annual overall use and the accumulated annual demand of each fuel in that year.

Storage Equations

The integration of energy storage within the OSeMOSYS framework follows a logical progression that translates instantaneous power flows into a continuous energy storage. The process begins by quantifying the energy entering (StorageCharge) and leaving (StorageDischarge) each storage facility (s) in each timeslice (l). The model evaluates the RateOfActivity of all technologies designated as storage interfaces, those capable of either charging or discharging the energy capacity of the battery, in each time slice. Since these technologies operate at a specific rate, the model converts this activity into a discrete energy quantity by multiplying it by the YearSplit, representing the fraction of the year that each time slice occupies. This ensures that the duration of each period is correctly accounted for when calculating the total volume of energy moved.

The balance of the storage system in each time slice is then determined by the net difference between these charging and discharging flows. Within any given time slice, a positive net balance indicates that the system is accumulating a surplus, while a negative balance means that the storage is acting as a net energy supplier to meet demand. To track the actual state of charge at specific moments, the model define the StorageLevel, by aggregating these net balances across the modelling horizon. Because OSeMOSYS uses representative time slices rather than a continuous chronological line, it applies a specialized mapping called StorageInflectionTimes to reconstruct the sequence of events. This logic ensures that the energy level at any time point only includes the accumulation from periods that chronologically precede it.

The operational feasibility of the system is maintained through strict physical boundaries. The model calculates the total available storage capacity each year, defined as the StorageUpperLimit, which is the sum of the AccumulatedNewStorageCapacity and the ResidualStorageCapacity for each year. Conversely, the StorageLowerLimit represents the technical minimum energy level and is determined by multiplying the MinStorageCharge factor by the total StorageUpperLimit. The storage level in each time period has to be always with the range given by the StorageUpperLimit and the StorageLowerLimit.

To ensure physical consistency within the representative time slices, the model imposes specific boundary conditions based on the storage type:

- Daily Storage (e.g., Batteries): The model imposes a cyclic boundary condition where the storage level at the end of the representative daily sequence is linked back to the start. This implies that the Net Energy Change over the 24-hour period must be zero, ensuring the battery is ready for the next day's cycle.

- Yearly Storage: The mapping follows an annual cycle, allowing the model to shift energy surpluses across different seasons to balance the system on a yearly scale.

By satisfying these constraints simultaneously, OSeMOSYS identifies the optimal storage strategy, in terms of new storage capacity and storage charge/discharge, that minimizes total system costs.

Activity and Capacity Constraints

- Total Capacity Constraints: Ensures that the total capacity of each technology in each year is greater than and less than the user-defined parameters TotalAnnualMinCapacityInvestment and TotalAnnualMaxCapacityInvestment respectively. The TotalCapacityAnnual for each technology, each year is computed as the sum between the AccumulatedNewCapacity and ResidualCapacity.
- New Capacity Constraints: Ensures that the new capacity of each technology installed in each year is greater than and less than the user-defined parameters TotalAnnualMinCapacityInvestment and TotalAnnualMaxCapacityInvestment respectively.
- Annual Activity Constraints: Ensures that the total activity of each technology over each year is greater than and less than the user-defined parameters TotalTechnologyAnnualActivityLowerLimit and TotalTechnologyAnnualActivityUpperLimit respectively.
  The TotalTechnologyAnnualActivity is computed as the sum over all the time slices of the product between RateOfTotalActivity per the YearSplit, computed for each time slice.
- Total Activity Constrainst: Ensures that the total activity of each technology over the entire model period is greater than and less than the user-defined parameters TotalTechnologyModelPeriodActivityLowerLimit and TotalTechnologyModelPeriodActivityUpperLimit respectively.

Emission Accounting

The model calculates the emissions generated by each technology each year based on its operational activity. By applying a specific emission activity ratio to the total annual activity of a technology, the model identifies the volume of pollutants produced across different modes of operation. These values are then aggregated to determine the total annual emissions for each technology and, subsequently, for the entire region.

The model also manages the economic consequences of these environmental impacts by calculating emission penalties. When a penalty or carbon tax is defined for a specific pollutant, OSeMOSYS multiplies the total annual emissions of a technology by the penalty rate to derive a technology-specific cost. To ensure consistency with the overall cost-minimization objective, these penalties are discounted back to the base year of the study, with the discount rate applied to the middle of the year in which the costs are considered.

Finally, the framework ensures that the energy system complies with predefined environmental targets through the imposition of limits. These constraints can be applied at two different temporal scales:

- Annual Emission Limits: These ensure that the sum of endogenous and exogenous emissions in a given year does not exceed a stipulated maximum.
- Model Period Emission Limits: These caps the cumulative emissions produced over the entire modeling horizon, allowing the model to optimize the timing of emissions as long as the total budget is respected.

Accounting Technology Production/Use

The model calculates the total volumes of energy produced and consumed by each technology, for each fuel, in each time slice by multiplying their respective production and use rates by the proportional duration of each time slice within a given year.

In particular, the rate of production for each fuel, technology and time slice is computed as the product by the rate of activity and the output activity ratio for that technology and fuel. Conversely, the rate of use for each fuel, technology and time slice is computed as the product of the rate of activity and the input activity ratio for that technology and fuel.

The model calculates the total volumes of energy produced and consumed by each technology, for each fuel, over the year summing the production and the use defined over each time slice.

3.4.6. Opeartional Logic

The operational core of OSeMOSYS is defined as a system-wide, simultaneous linear optimization problem. Built on a least-cost optimization logic, OSeMOSYS identifies the optimal energy supply mix by determining the necessary generation and storage capacity and energy delivery required to fulfil service demands across all years and time steps. By evaluating various technological pathways, the framework ensures that demand is consistently met while simultaneously minimizing the total discounted system costs throughout the study's horizon. The solver processes the entire planning horizon (e.g., 2024–2050) as a single monolithic matrix, aiming to identify the unique vector of decision variables that minimizes the Total Discounted Cost. The logical workflow proceeds through strictly defined mathematical phases, constructing the feasible space before identifying the optimal trajectory mandated by demand.

While OSeMOSYS is conceptually driven by two primary classes of decision variables, Investment (NewCapacity) and Operation (RateOfActivity), the mathematical dimensionality of the optimization problem is significantly larger. The total number of decision variables, or degrees of freedom, is determined by the Cartesian product of the model's fundamental sets: Years (y), Technologies (t), Time Slices (l), Modes of Operation (m), and Regions (r).

The search for the optimal solution in a linear programming model begins with the definition of the Feasible Region. This is a multidimensional geometric space in which all decision variables simultaneously satisfy every constraint imposed by the system. Each energy balance equation or physical limit, such as the relationship between the rate of activity and the total annual capacity, acts as a hyperplane that binds this space. This transforms the solution space into a convex polytope with flat faces, where every point within its boundaries represents a technically feasible system configuration.

The Objective Function, which in OSeMOSYS targets the minimization of the Total Discounted Cost, acts as a directional compass that guides the solver toward the economically advantageous face or vertex of the polytope. By utilizing algorithms such as the Simplex method, the solver systematically explores the vertices of this multidimensional solid, moving along the edges to test different combinations of new capacity installations and operational flows. Because the region is convex and the objective function is linear, optimization theory guarantees that the vertex where the function value can no longer be reduced represents the global optimum, the minimum cost solution for the entire analyzed energy system.

Within this constructed space, Exogenous Demand acts as the primary binding constraint (or forcing function) that prevents the solver from converging on a trivial zero-cost solution. The SpecifiedAnnualDemand is projected onto representative time slices via the SpecifiedDemandProfile. This requirement is enforced by the Energy Balance constraints, which mandate that for every fuel, time slice, and year, production must satisfy both exogenous demand and endogenous inter-technological use.

Once the feasible space is bounded and the demand constraint is active, the solver performs a simultaneous competitive evaluation across all time slices to determine the optimal technology mix. The selection logic remains strictly governed by the objective function, ensuring that the final configuration represents the most efficient allocation of resources to meet the system's energy needs over the entire planning horizon.

The optimization engine employs a merit-order logic based on marginal costs and complex investment trade-offs. For each time slice, the solver calculates the cost of supplying the next unit of energy by aggregating variable costs, fuel expenses, determined via the input activity ratio, and any applicable emissions penalties associated with the rate of activity of each technology. The model consistently prioritizes the technology with the lowest marginal cost to meet the instantaneous demand. Simultaneously, the model evaluates whether investing in new capacity, thereby incurring upfront capital costs, is more economically efficient than utilizing existing generation assets that may have higher operating expenses. Benefiting from perfect foresight, the solver anticipates future cost evolutions and policy changes, optimizing the specific timing of investments over the entire operational life of the technologies.

A fundamental structural characteristic of OSeMOSYS is the decoupling of the temporal resolution used for strategic planning versus operational dispatch. Capacity expansion decisions, representing the "strategic time," are modelled with an annual granularity. The decision variable for new capacity is indexed solely by year, technology, and region, omitting any sub-annual indices. This implies that the optimization algorithm treats capacity deployment as a discrete step function; when the solver elects to install capacity in a specific year, the model assumes this infrastructure is fully commissioned and available to operate at its nominal rating starting from the very beginning of that year. The capacity is available uniformly across all time slices of that year, which precludes the modelling of intra-annual construction delays or seasonal commissioning.

Conversely, the utilization of this capacity, the "dispatch time", is modelled with sub-annual granularity. The rate of activity variable includes the time slice index, allowing the solver to vary the output of the fixed capacity stock dynamically to match the specific profile of demand or resource availability within the year.

The representation of energy storage in OSeMOSYS is governed by a dedicated set of constraints that enable inter-temporal energy arbitrage. Unlike standard technologies that must balance supply and demand instantaneously within a single time slice, storage facilities introduce a form of "memory" into the system, allowing energy produced in one period to be shifted and consumed in another. This logical structure consists of two distinct entities interacting via coupling parameters:

- The Interface Technologies: These are standard technology components responsible for the power flow, measured in power units. Their operation is defined by the rate of activity.
- The Storage Facility: This is an abstract "reservoir" responsible for holding the energy stock, measured in energy units. Its state is defined by the storage level.

The flow of energy into and out of the storage is not direct but is mediated by these linked technologies. The model translates the operational power of these technologies into discrete energy quantities using the duration of the time slice, the year split. The total energy entering a storage unit in a specific time slice is calculated by summing the activity of all connected charging technologies, while the energy extracted is derived from the activity of discharging technologies. The net energy flux for the time slice is then determined as the algebraic difference between the total energy charged and discharged.

The core of the storage logic is the storage level constraint, which ensures physical consistency across time. Since OSeMOSYS operates with quasi-chronological time slices rather than a continuous clock, it utilizes storage inflection times to map the logical sequence of events. The level of energy at any specific boundary instance is calculated as the cumulative sum of all net charges occurring throughout the year, properly integrated over the duration of their respective time slices to ensure the state of charge remains within technical limits.

$$\mathrm{StorageLevel}_{s,b,r} = \sum_{l,y}\left(\frac{\mathrm{NetStorageCharge}_{s,y,l,r}}{\mathrm{YearSplit}_{y,l}}\right) * \mathrm{StorageInflectionTimes}_{y,l,b} \quad (3.3)$$

Equation (3.3) acts as the temporal bridge: it forces the solver to ensure that if energy is withdrawn in a later time slice (creating a negative NetStorageCharge), it must have been accumulated in previous slices to maintain a non-negative balance.

The optimization within the OSeMOSYS framework ensures that the physical sizing of the reservoir (the energy storage capacity of the battery) is respected at every instant by bounding the state of charge through two primary energy capacity limits.

$$\mathrm{StorageLowerLimit}_{s,r} \leq \mathrm{StorageLevel}_{s,b,r} \leq \mathrm{StorageUpperLimit}_{s,r} \quad (3.4)$$

The Storage Upper Limit represents the maximum allowed level of a stored commodity and directly defines the total energy dimension of the storage facility; it is calculated as the sum of newly installed and pre-existing residual capacities. Conversely, the Storage Lower Limit defines the technical minimum level, calculated as a function of the total capacity and a user-defined minimum charge ratio, ensuring the system maintains a functional operational baseline. By solving these constraints simultaneously with the system-wide energy balance, the model endogenously identifies the Optimal Storage Strategy, determining exactly when to charge during periods of low marginal cost and when to discharge during periods of high cost or scarcity to minimize the total discounted cost.

OSeMOSYS, and specifically MUIO, distinguishes storage technologies based on their temporal operational logic, primarily categorizing them into daily and yearly systems. For Daily Storage (e.g., utility-scale batteries) characterized by high cycling frequency, the model enforces an intra-diurnal operational logic where a cyclic boundary condition links the energy level at the end of a representative day back to its start. This implies that the net energy change over the day must be zero, preventing energy carry-over between distinct chronological days within the same season and ensuring the battery size is optimized to be large enough to capture the maximum energy surplus, often from solar peaks, before the discharge phase begins. In the context of daily cycling logic, the imposition of a MinStorageCharge ratio establishes a functional baseline for the operational profile. Driven by the objective of capital cost minimization, the solver anchors the starting state-of-charge of the representative day to coincide strictly with this technical floor, that is the product of the MinStorageCharge with the Total Storage Capacity at the start of the representative day.

In contrast, Yearly Storage (e.g., large hydro reservoirs) is designed to shift energy across different time slices throughout the entire year; while the energy balance must still close, the boundary is defined at the annual level, allowing the model to store seasonal surpluses to be utilized months later to balance long-term requirements. To initialize the simulation, the parameter StorageLevelStart provides the necessary scalar value to begin the recursive calculation chain. This parameter is utilized exclusively at the very first time slice of the starting year of the modelling period.

4 Modelling the Long-term Evolution of the European Power Sector: A 2050 Optimization Approach

This chapter details the implementation of an aggregated linear optimization model for the continental European power system with a time horizon extending to 2050. The model is developed using the OSeMOSYS framework through the MUIO interface, as introduced in 3.3.

The primary objective of the model is to identify least-cost trajectories for both capacity expansion and dispatch operation, ensuring that the projected increasing electricity demand is met at the minimum total discounted cost. The study evaluates several pathways based on the World Energy Outlook 2024 (WEO 2024) scenarios (STEPS, APS, NZE), incorporating the evolution of Capex, efficiencies, and fuel costs, alongside a progressively increasing carbon tax to assess their impact on the optimal technology mix.

The following sections outline the problem statement, the research questions, the methodological assumptions, the Reference Energy Systems and the Scenario modelled.

4.1. Problem Formulation and Research Objectives

4.1.1. Problem statement and research questions

The urgent need to mitigate climate change is leading Europe to a radical transformation of its energy landscape, aiming to reach climate neutrality by the end of 2050. This transition requires the adoption of clean power technologies to decarbonize the electric power production sector, shifting from conventional fossil-fuel-based generation toward a system dominated by Variable Renewable Energy (VRE) sources with storage.

In this context, long-term energy planning becomes a very complex task. Policymakers rely on sophisticated energy models to identify the most cost-effective pathways for decarbonization. However, while hyper-complex models, such as those used by the International Energy Agency (IEA) for the World Energy Outlook (WEO), provide highly detailed results, they often operate as "black boxes" due to their immense computational requirements and proprietary structures.

Therefore, the core problem addressed in this thesis is to determine whether a simplified, aggregated linear optimization open-source model, developed via the OSeMOSYS framework, can provide strategic insights and energy trajectories that are consistent with the more complex benchmarks provided by the WEO 2024 for Europe.

Specifically, this research aims to solve a cost-minimization problem for the European power sector, covering continental Europe geographical definition of the IEA, over a time horizon reaching 2050. The choice to adopt Continental Europe as the geographical perimeter, rather than the political boundaries of the European Union (EU), is grounded in the necessity for methodological stability. The EU political framework is inherently variable; within a time horizon reaching 2050, it is highly probable that the Union will undergo further expansions, such as the potential accession of the Western Balkans or Ukraine, or administrative shifts, as exemplified by the historical precedent of Brexit. Modeling Continental Europe provides a fixed and immutable geographic reference. This approach prevents the 2050 simulation results from being distorted by changes in administrative borders, thereby ensuring data consistency and comparability across the entire temporal horizon.

Furthermore, nations such as Switzerland, Norway, and the United Kingdom, despite being outside the EU political perimeter, remain fundamental pillars of the European energy balance, inevitably influencing also EU behavior and energetic policies.

The study is structured to address the following research questions:

- Can a simplified, aggregated linear optimization model, focused solely on cost minimization, produce trends and outputs consistent with those of the IEA WEO 2024 Europe scenarios given a consistent set of input parameters?
- Building on the modeling framework established for the benchmarking in RQ1, identify the long-term systemic implications and structural shifts arising from the Continental European power sector's evolution across the three modeled scenarios.

By answering these questions, this analysis aims to validate the use of open-source, aggregated and simplified cost-optimization models for large-scale energy planning, providing a critical assessment of their reliability for the ambitious 2050 net-zero targets.

4.1.2. Logical Framework of the Optimization Problem

The design optimization problem can be described as follows:

Given:

- a catalogue of power technologies (Renewables, Thermal, and Storage) characterized by specific techno-economic parameters (CAPEX, fixed/variable O&M, efficiencies, availability and capacity factors),
- the existing European power generation capacity and its predetermined technical decommissioning schedule based on the average age of plant and expect lifetime,
- the expected evolution of electrical demand,
- three distinct scenarios derived from the IEA WEO 2024, each populated with a set of scenario dependent input parameters,
- potential and deployment limits for each technology,
- resource and activity limits on the total production of specific energy sources,

Determine:

- The optimal timing and scale of *New Capacity* installations for both generation and storage assets,
- The *Rate of Activity* for each technology and the charge/discharge for storage units in every time-slice and annually,

So as to minimize:

- The total discounted system cost, that is the sum of all discounted capital expenditures, operational costs, fuel costs, and emission penalties, minus the salvage value, over the 2024–2050 modelling horizon, while satisfying energy balances and capacity adequacy both annually and in each time slices and the other user defined constraints.

4.2. Methodology and modelling framework

This section outlines the methodological framework adopted for the development and execution of the optimization model. It begins with introducing the Reference Energy System (RES), which defines the structural architecture of the entire modeling process. Subsequently, the methodological assumptions underlying the model are detailed, followed by a description of the specific scenarios.

4.2.1. Reference Energy System (RES) and System Topology

The Reference Energy System (RES) for the European power model is presented in Figure 4.1. The RES is a graphic abstraction of the modelled energy system, and it maps the flow and conversion of energy commodities from primary supply to end-use demand. Table 4.1 provides the description of the Reference Energy System, as well as the acronyms and abbreviations of each technology and demand sector. Quantitative information regarding Installed Capacity and Electricity Production for the base year 2024 are detailed in Chapter 5.

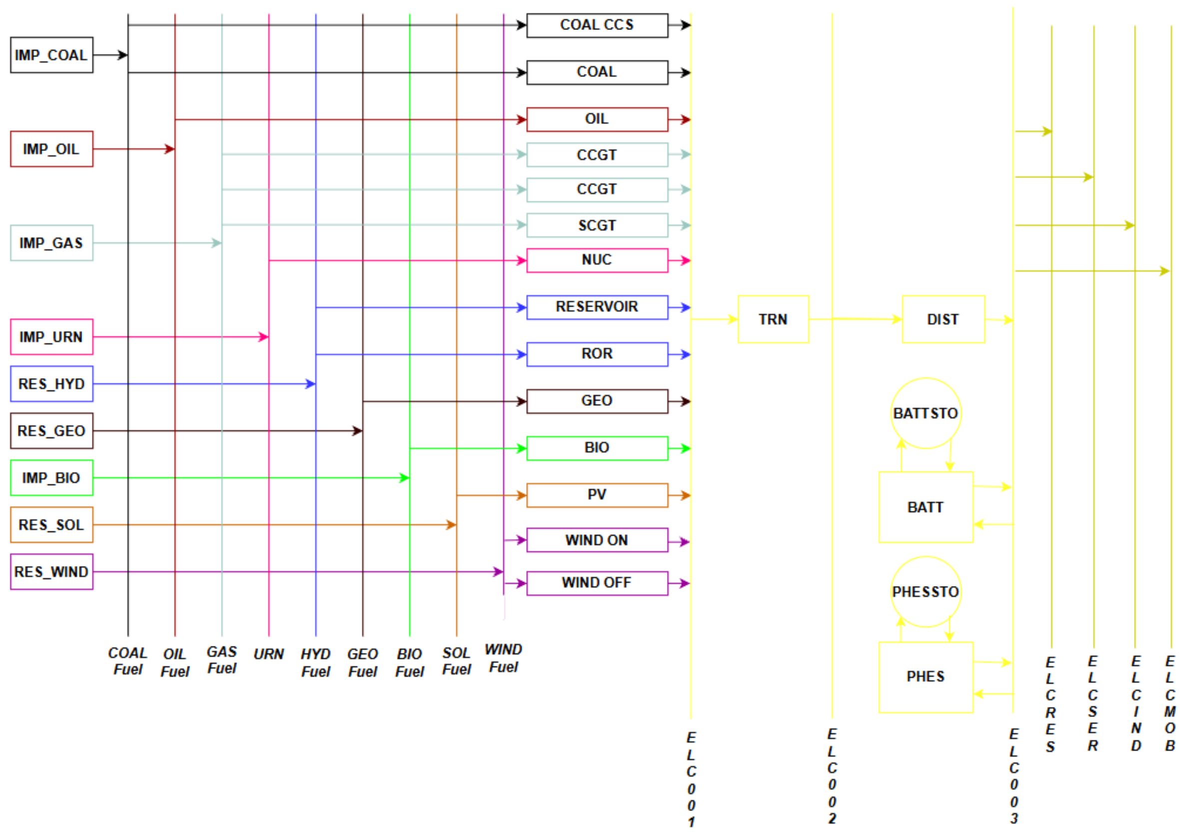

Figure 4.1: European Reference Energy System

Table 4.1: Reference Energy System Description

Code	Description	Category
COAL Fuel, OIL Fuel, GAS Fuel, URN	Fossil Fuel (Coal, Natural Gas, Oil, Uranium)	Primary Commodity
SUN Fuel, WIND Fuel, HYD Fuel, GEO Fuel	Solar, Wind, Hydro, Geothermal renewable potentials	Primary Commodity
IMP_COAL, IMP_OIL, IMP_URN, IMP_GAS	Primary Fossil Fuel Supply (Coal, Natural Gas, Oil, Uranium)	Technology (Supply)
IMP_BIO	Primary Biomass Supply	Technology (Supply)
RES_HYD, RES_SOL, RES_GEO, RES_WIND	Solar, Wind, Hydro, Geothermal Renewable Potentials	Technology (Supply)
BIO Fuel	Biomass Fuel	Primary Commodity
ELC_001	Primary Electricity (Output from Power Plants)	Intermediate Commodity
ELC_002	Secondary Electricity (Post-Transmission level)	Intermediate Commodity
ELC_003	Tertiary Electricity (Post-Distribution level)	Intermediate Commodity
ELC_IND	Final Electricity Demand – Industrial Sector	Demand Sector
ELC_RES	Final Electricity Demand – Residential Sector	Demand Sector
ELC_SER	Final Electricity Demand – Services/Commercial Sector	Demand Sector
ELC_MOB	Final Electricity Demand – Mobility/Transport Sector	Demand Sector
COAL	Coal-fired Power Plants	Technology (Conversion)
OIL	Oil-fired Power Plants	Technology (Conversion)
CCGT	Natural Gas Combined Cycle Plants	Technology (Conversion)
SCGT	Natural Gas Single Cycle Plants	Technology (Conversion)
NUC	Nuclear Power Plants	Technology (Conversion)
RESERVOIR	Reservoir Hydro Power Plant	Technology (Conversion)
ROR	Run-of-River Hydro Power Plant	Technology (Conversion)
GEO	Geothermal Power Plants	Technology (Conversion)
BIO	Biomass-to-Power Plants	Technology (Conversion)
PV	Solar Photovoltaic Plants	Technology (Conversion)
WIND ON, WIND OFF	Onshore Wind Turbines and Offshore Wind Turbines	Technology (Conversion)
TRN	High-Voltage Transmission Network	Infrastructure
DIST	Low-Voltage Distribution Network	Infrastructure
BATT	Lithium-ion Battery Energy Storage Systems	Technology (Conversion)
BATTSTO	Lithium-ion Battery Energy Storage Systems	Storage Technology
PHES	Pumped Hydro Energy Storage	Technology (Conversion)
PHESTO	Pumped Hydro Energy Storage	Storage Technology

In Figure 4.1 all lines represent energy carrier and service, while technologies are represented by boxes. In OSeMOSYS an energy system is represented by a set of technologies and energy-carriers, that include not only commodities but also energy services and proxies. Each technology either uses and/or produces an energy carrier. A resource extraction or import process is intended in OSeMOSYS as a technology that produces an energy carrier, while demand service is intended in OSeMOSYS as a technology that uses an energy carrier, such as electricity. A power plant is represented as a technology that uses an energy carrier, such as coal, and produces another energy carrier, such as electricity. In OSeMOSYS all energy system components are set up as 'technology ', and the technology includes any element of the energy system which changes energy from one form to another, uses it or produces it.

The RES provided in Figure 4.1 has to be read from left to right and includes:

- Primary Energy Supply: the section on the left of the diagram identifies the primary resources, including fossil fuel imports (IMP) (coal, gas, oil, uranium), as well as renewable potentials (RES) (solar, wind, hydro, biomass, and geothermal).

- Transformation Technologies: these resources are linked via energy lines to specific conversion technologies, represented by the central blocks.
- Infrastructure and Flexibility: The model explicitly accounts for the transmission and distribution stages. Crucially, RES integrates flexibility assets, specifically Battery Energy Storage and Pumped Hydro Energy Storage, which are essential for balancing the intermittent nature of renewable generation. Batteries and PHES are modelled separating power and storage components.
- Final Demand: The energy flow terminates in the four distinct electricity demand sectors: Residential, Services, Industry, and Mobility.

It is important to emphasize that both Coal CCS and Gas CCS technologies are available within the model starting from 2025. It was assumed that these technologies do not contribute to the 2024 baseline (the year of calibration), given their currently limited deployment and early stage of commercial availability.

Detailed information regarding the specific techno-economic characteristics of the conversion technologies, as well as the disaggregated projections and load profiles for each electricity demand sector, are analyzed and justified in the subsequent sections of this methodology.

4.2.2. Methodological Assumptions

The development of the optimization model is based on a set of core methodological assumptions introduced to balance computational efficiency with the strategic objectives of the study.

Geographic Scope and Regional Aggregation

The model consider the geographical perimeter of Continental Europe as defined by the IEA WEO 2024 (IEA, 2024), which includes the European Union regional grouping along with Albania, Belarus, Bosnia and Herzegovina, Gibraltar, Iceland, Israel, Kosovo, Montenegro, North Macedonia, Norway, the Republic of Moldova, Serbia, Switzerland, Türkiye, Ukraine, and the United Kingdom. For the purposes of this study, this vast area is modelled as a single, aggregated region. This single-node approach significantly reduces the computational complexity while allowing for a clear focus on the long-term evolution of the overall European technology power mix.

Network Representation: The 'Copper Plate' Hypothesis

The modelling of the European power system relies on the 'copper plate' hypothesis. This assumption implies that there are no internal grid bottlenecks, congestion, or transmission constraints within the modelled region. It is assumed that sufficient grid capacity is available at both the transmission and distribution levels to facilitate the optimal flow of electricity. The model does not account for the investment costs of additional grid expansion as the network capacity is assumed to be largely sufficient to support all necessary energy flows.

However, the model does not entirely overlook the power grid; both transmission and distribution infrastructures are represented through an efficiency factor, accounting for technical losses within the system.

Strategic Autonomy: The 'Island Mode' Assumption

A key assumption of the model is that the modelled European region operates in 'Island Mode'. This means that the model assumes zero electricity imports or exports with regions outside the defined European perimeter. This choice is technically supported by the analysis of the Statistical Factsheet 2024 (ENTSO-E, 2025) .

Specifically, the data indicates that the electricity exchanged in 2024 out of the ENTSO-E perimeter is less than 1-2% of the total trade, making the impact of external exchanges negligible for the purposes of this long-term optimization.

Temporal and Profile Synchronization

To maintain a manageable level of complexity, the model disregards time zone differences between member states. Consequently, load profiles and Variable Renewable Energy (VRE) generation profiles (solar and wind) are assumed to be synchronized across a single continental reference hour. This simplification allows for a consistent temporal assessment of the balance between supply and demand across the entire single region.

Temporal Framework and Planning Horizon

The modelling analysis begins in 2024, which serves as the historical base year due to the availability of a comprehensive and consistent dataset for the European energy system. The planning horizon extends to 2050, with an annual resolution that considers every year within the 2024-2050 range.

This timeframe is selected to align with the European Net Zero Emissions (NZE) commitments and to ensure direct comparability with the long-term scenarios established in the IEA WEO 2024.

Time Slice Definition

The model does not optimize across all 8,760 hours each year within the time horizon. The optimization is restricted to a set number of time slices per year to reduce computational efforts, assuming uniform behavior within each time slice (e.g., treating every 12:00 PM hour in summer workdays as identical).

To capture the intra-annual variability of both electricity demand and renewable energy generation, the year has been discretized into 144 time slices. This temporal structure is defined by the combination of three seasonal categories, two-day types, and a full 24-hour daily profile:

- Seasons: Summer, Winter, and an intermediate 'Mid-season' (representing Spring and Autumn).
- Day Types: Workdays (Monday to Friday) and Weekends (Saturday and Sunday).
- Daily Time Bracket: Each hour of the representative day is modelled individually.

The selection of 144 time slices (3 season * 2 day types * 24 daily time bracket) represents an optimal trade-off between high-resolution accuracy and computational efficiency. This resolution is specifically designed to reflect the complex dynamics of the European power sector. It allows the model to accurately represent the electrical demand dynamics, capturing hourly peaks, weekly cycles (Workday vs. Weekend), and seasonal shifts across different modelled sectors. This resolution allows also the model to capture renewable generation variability, characterized by hour and seasonal variations.

Technology Portfolio and technical assumptions

The model represents the European power sector through a comprehensive portfolio of generation and storage technologies, strictly aligned with the IEA WEO 2024 technology set. To ensure the reliability of the long-term projections, the study focuses exclusively on commercially mature technologies that are currently deployed.

A key assumption is the aggregation of technologies into representative reference units, characterized by European average performance metrics and costs. While the available technology set remains consistent across all modelled scenarios, their cost and efficiency projections over the period vary in the different scenarios. Furthermore, it is assumed that no radically new or unproven technologies will enter the market during the 2024–2050 analysis period, with the only exception of CCGT and Coal Power Plant both equipped with Carbon Capture and Storage capabilities. It is important to underline that these technologies became available for the system from 2025 (Flöer, 2025), with different deployments and penetration rate according to the scenario. In addition, it is important to stress that the optimizer can freely decide if and eventually invest in these new technologies.

The specific technology catalogue includes:

- Renewable and Carbon-Free Generation: Solar PV, Onshore and Offshore Wind, Hydropower (Run-of-river and Reservoir), Conventional Geothermal (assumed to be effectively carbon free), Biomass (assumed to be effectively carbon free) and Nuclear power.
- Thermal Generation: Conventional plants fueled by Coal, Natural Gas (both Combined Cycle Gas Turbines - CCGT and Single Cycle Gas Turbines - SCGT), and Oil, all modelled without Carbon Capture and Storage (CCS) capabilities. In addition are also added CCGT and Coal Power Plant with Carbon Capture and Storage (CCS) capabilities.
- Flexibility and Storage Solutions: To manage the variability of renewable sources, the model can invest in utility-scale Lithium-ion batteries and Pumped Hydro Storage (PHS). Storage technologies are modelled considering power and storage component.

Concentrated Solar Power (CSP), as well as other marginal renewable sources such as waves, ocean, and tidal power, have been excluded from the explicit modelling framework. This simplification is justified by their minimal contribution to the current European energy mix, (with CSP representing less than 1% of the total solar fleet) and by their high geographic concentration, which makes their impact on macro-regional dynamics negligible relative to the additional computational effort (JRC, 2024).

Regarding photovoltaic technology, a single, highly aggregated Solar PV technology was modeled rather than differentiating between specific configurations (such as rooftop or utility-scale systems). This choice was made to simplify the assessment of a representative Capacity Factor (CF). By utilizing historical European-wide averages for both total electricity production and installed capacity, it was possible to derive a robust, mean capacity factor that captures the average solar potential across the continent without requiring site-specific datasets.

For renewable energy sources (wind, solar, and hydro), the capacity factors are assumed to be representative and constant throughout the 2024–2050 period. The model simplifies the analysis by ignoring potential long-term impacts of climate change on weather patterns, such as variations in wind speed, solar irradiance, or hydrological cycles.

In addition, the model adopts an ‘overnight construction’ assumption. This means that new capacity is assumed to be built and become fully operational instantaneously in the year the investment decision is made, disregarding the real-world lead times (planning and construction periods) typical of large-scale energy projects. In the model no ‘life extension’ measures are considered.

Sectoral Demand Segmentation and demand-side assumptions

The model is characterized by a specific sectoral demand segmentation. To capture the distinct dynamics of electricity consumption across the continent, the total European demand is disaggregated into four key sectors: Residential, Services, Industry, and Transport (Mobility).

The demand modeling is based on the following assumptions and parameters:

- The percentage disaggregation of demand is assumed to change over time, from 2024 to 2050, following a linear profile. Specifically:
    - Residential Sector: decreases from 29% in 2024 to 18% in 2050.
    - Services Sector decreases from 32% in 2024 to 28% in 2050.
    - Industry Sector: decreases from 36% in 2024 to 31% in 2050.
    - Transport (Mobility) Sector increases significantly from 3% in 2024 to 23% in 2050.

  The 2024 baseline shares are in accordance with (IEA, 2023), while the 2050 projections are an extrapolation to 2050 of the evolution projected by (TERNA, 2025).
- It is assumed that this percentage distribution of electricity demand remains uniform across the different scenarios (STEPS, APS, NZE), even though the absolute total electricity demand varies in each of them.
- Electricity demand is an exogenous input, treated as perfectly inelastic. Furthermore, the load profiles for each sector are assumed to remain constant over the simulation horizon, assuming no significant demand-side management or mitigation measures.
- To accurately represent temporal consumption patterns, the following profiles are adopted:
    - Residential electricity sector profile: as reported by (NATCONSUMERS, 2016), (Ali Hashemifarzada, 2019).
    - Services sector profile: as reported by (Frits Møller Andersen, 2024).
    - Urban electric charging (Transport): as reported by (Christopher Hecht, 2023).
    - Industrial sector electricity profile: as reported by (Patrick Dehning, 2019).

The definition of the SpecifiedDemandProfile parameter for each time slice of every sector is calibrated to reproduce these historical load patterns as closely as possible.

The selection of time slices ensures that daily, weekly, and seasonal variations are effectively captured. While total electricity demand grows in each scenario according to the sectoral projections, the timing of peaks and troughs are assumed to remain consistent with historical patterns, reflecting established consumption behaviors.

Economic Linearity and Operational Abstraction

A fundamental assumption of the model is the absence of economies of scale, due to the linear programming nature of the model. This implies that the unit cost of technology (e.g., €/kW) remains constant regardless of the total capacity installed in a single investment step. Whether the model decides to install 1 MW or 10 GW of specific technology, the marginal cost per kilowatt remains unchanged.

To mitigate this limitation and reflect real-world market dynamics, the model incorporates exogenous cost reductions projections (learning curves). These cost trajectories are scenario-specific: in more ambitious decarbonization scenarios (such as NZE), the model assumes steeper cost declines for renewable energy and storage technologies. This reflects the global trend where increased deployment, technological innovation, and international cooperation lead to significant price reductions over the planning horizon.

As a long-term energy planning tool, OSeMOSYS prioritizes the strategic evolution of the European power fleet over short-term operational details. Consequently, the following operational constraints are not considered in their base formulation and therefore in this analysis:

- Unit Commitment: The model does not account for the specific start-up and shut-down times or the associated costs of individual power plants.
- Ramping Limits: Constraints regarding how quickly a plant can increase or decrease its power output (ramp rates) are omitted.

This level of abstraction is consistent with an aggregated, continental-scale model. By focusing on annual energy balances and hourly capacity requirements across representative time slices, the model provides a high-level overview of the necessary capacity expansion. This approach ensures computational feasibility while capturing the fundamental shifts in the energy mix required to meet 2050 targets.

Economic and Environmental Assumptions

Specific assumptions have been introduced regarding economic and environmental accounting.

Firstly, the model operates in constant prices, neglecting the effects of general inflation over the planning horizon. This assumption allows the analysis to focus exclusively on the real price evolution.

Secondly, the environmental assessment is strictly limited to direct operational emissions (Scope 1) resulting from fuel combustion during electricity generation. Consequently, emissions associated with the manufacturing, construction and end-of-life phases of power plant are excluded from the model's analysis. Furthermore, CO_2 is considered the only emission category within the model's environmental accounting. This choice reflects the primary focus of European climate policy and carbon pricing mechanisms on greenhouse gas reduction in the power sector.

Within this modelling framework, only fossil-fuel-based technologies are categorized as emissive sources, whereas biomass and geothermal energy are assumed to be carbon-neutral. This assumption for biomass is based on the principle that the atmospheric carbon dioxide sequestered during its growth phase effectively offsets or exceeds the CO_2 released during its energy conversion process, maintaining a closed-loop biogenic carbon cycle (IEA Bioenergy, 2018).

Similarly, geothermal power is treated as carbon-neutral because these plants do not rely on fuel combustion to generate electricity; while they may release negligible amounts of sulphur dioxide and carbon dioxide trapped within geological formations, their environmental impact is minimal, emitting approximately 97% less acid-rain-causing sulphur compounds and about 99% less CO_2 than fossil fuel power plants of comparable capacity (EIA, 2022).

Perfect Foresight and Inter-temporal Optimization

The model operates under the logic of perfect foresight (or inter-temporal optimization). This methodological approach assumes that the solver within the model have complete information regarding future technology costs, fuel prices, and policy constraints throughout the entire planning horizon (2024–2050). Consequently, the optimizer identifies the most cost-effective investment pathways by considering the long-term impacts of current decisions. The model evaluates the costs and constraints of every year from 2024 to 2050 in a single computational step, identifying the least-cost investment pathway. While this represents an idealization of real-world market behavior, where uncertainty and limited foresight dominate, it is a standard assumption in long-term energy planning and is an intrinsic characteristic of OSeMOSYS.

4.2.3. Scenario Definition

Three different scenarios have been modelled for the European power sector, as in the IEA World Energy Outlook (WEO) 2024. These are:

- Stated Policies Scenario (STEPS),
- Announced Pledges Scenario (APS),
- Net Zero Emissions by 2050 Scenario (NZE).

Specifically, the NZE scenario in this model is designed to achieve a zero-emission power sector by 2050 without the utilization of Direct Air Capture.

The difference between these three different scenarios reflects the way in which these scenarios are defined in WEO 2024. While the Stated Policies Scenario and the Announced Pledges Scenario are exploratory scenarios, the Net Zero Emissions by 2050 Scenario is a normative scenario. These intrinsic differences are maintained in the definition of this analysis. For the two exploration scenarios no emission limit trajectory is imposed, while for the target scenario a linear trajectory reaching zero CO_2 emission in 2050 is imposed to the model, starting from the 2024 emission level.

The scenarios are primarily differentiated by electricity demand trajectories, annual emission penalties, fuel and technologies cost projections, max capacity investment per year and technology, max variation of electricity production per year and technology. Constraints on maximum installable capacity and production have been applied to reflect the physical limitations of specific energy resources.

To ensure consistency and comparability between scenarios, they share common baseline parameters: the 2050-time horizon and time slices definition, the mix of technologies considered, the base-year installed capacity, and the decommissioning trajectories for the existing fleet.

In addition, it is assumed that the four electricity demand sectors maintain the same percentage growth across all scenarios and that their respective load curves remain constant in shape through 2050 and uniform between scenarios. Similarly, the Capacity Factors for renewable technologies are kept uniform across scenarios and constant over the entire modelling horizon, as also the availability factor of conventional non renewables technologies.

Comprehensive details regarding specific inputs, secondary data sources utilized when IEA data was unavailable, and further methodological insights for the scenario definition are provided in the chapter devoted to input parameters 3.4.3.

5 2024 Baseline: Model Calibration and Current System Architecture

The following section describes the model calibration procedure, a fundamental phase designed to ensure that the mathematical simulation accurately reflects the operational reality of the European power system for the base year 2024.

The process begins with the definition of a representative 2024 Reference Energy System (RES), which is structured to represent 2024 European empirical data, regarding installed capacity and electricity production, across the various aggregated technologies considered in the model. This RES serves as the essential foundational benchmark for the next calibration phase of the model.

After defining the RES, the model is populated with the technical and economic data for the year 2024, and a preliminary simulation for the base year alone is executed to observe the results generated endogenously by the solver. By comparing these outputs with the expected RES values for 2024, the model is calibrated by imposing a series of specific activity constraints on each technology. These constraints force the model to match the established RES, ensuring that the initial year of the simulation strictly aligns with the verified historical situation. This methodological approach guarantees that the future evolution of the energy system (2025–2050) originates from a solid, verified 2024 baseline that mirrors real-world operational conditions as closely as possible, thereby enhancing the reliability of the subsequent scenario projections.

Furthermore, during this preliminary phase, the efficiencies for the Transmission and Distribution (T&D) infrastructure are quantified. Total system losses are estimated as the discrepancy between the Total Net Electricity Generation 2024 of the established RES and the European Electricity Demand 2024. These aggregate losses are subsequently disaggregated and allocated between the transmission and distribution segments. This allocation allows for the specific calculation of individual efficiency coefficients for each network layer, ensuring that the model accurately reflects the energy dissipated during transport.

5.1. Current System Architecture Definition

5.1.1. Total Installed Capacity and Total Gross Electricity Production

The fundamental first step of the calibration phase consisted of aggregating and simplifying the 2024 European power sector into a limited set of technologies as defined in the Reference Energy System (RES) of the model Figure 4.1.

The primary objective of this process is to develop a representative RES of the European power sector that utilizes the same technologies as the model, while being defined by installed capacity and electricity generation values that are strictly coherent with real-world European 2024 data.

This reconstructed RES subsequently serves as the essential foundational benchmark for the initial model simulation, providing a verified reference against which the endogenous results of the solver are compared.

It is important to underline that this representative RES is strictly based on the 2024 technological landscape assumed for the model; as such, it does not include Carbon Capture and Storage (CCS) technologies, which are assumed to only be available for investment and deployment within the model starting from 2025.

The geographical perimeter of the representative RES is defined to align with the "Continental Europe" regional grouping established by the IEA World Energy Outlook 2024 (IEA, 2024). This scope encompasses the European Union member states along with Albania, Belarus, Bosnia and Herzegovina, Gibraltar, Iceland, Israel, Kosovo, Montenegro, North Macedonia, Norway, the Republic of Moldova, Serbia, Switzerland, Türkiye, Ukraine, and the United Kingdom.

For defining the installed capacity and electricity gross generation of the RES technologies, the (EMBER, 2024) and (IRENA, 2025) datasets served as the two primary sources. All entries and data sourced from these two databases underwent preliminary processing to match the IEA WEO 2024 perimeter, as they originally referred to different European geographical regions. Specifically, the Ember "Continental Europe" aggregate is modified by manually adding the contribution of Israel and explicitly excluding the Russian Federation, while the IRENA Europe dataset is adjusted by adding the contributions of both Israel and Türkiye.

For the 2024 baseline definition of the RES, (EMBER, 2024) is utilized to obtain the installed capacity and total electricity generation for nuclear, coal, and oil, the latter assumed to coincide with Ember's "other fossil fuel" category, as well as the installed capacity for solar PV and the total aggregate capacity and electricity generation for both the hydro and gas sectors. From (IRENA, 2025), the RES sourced the specific installed capacity and electricity generation for biomass and geothermal energy, the total installed capacity for onshore/offshore wind, and the specific Capacity Factors (CF) for both solar PV and onshore/offshore wind.

Because the technologies defining the Reference Energy System are more disaggregated than the sources reported in Ember, a critical subsequent step involved partitioning Ember's aggregate sources into granular technological categories to reflect their distinct operational roles.

For hydroelectric power, the total 2024 hydro capacity from Ember is partitioned using estimates from (Jignesh Shah, 2025), assigning 68% to reservoir and 32% to run-of-river capacity, while information regarding the installed capacity of pumped hydro is sourced directly from (IRENA, 2025).

To derive production, run-of-river generation is calculated by applying a capacity factor of 0.45 (IRENA, 2025) to the computed run-of-river hydroelectric installed capacity, reflecting its non-dispatchable nature, with reservoir production subsequently defined as the residual between Ember's total hydroelectric generation and the calculated run-of-river share.

Regarding natural gas, in the absence of granular reporting, total (EMBER, 2024) capacity and electricity generation are split by applying an assumed capacity repartition of 75% for CCGT and 25% for SCGT, with a corresponding assumed production repartition of 95% and 5% respectively, a subdivision that reflects the operational roles of CCGT as baseload/mid-load and SCGT as peaking plants.

For wind energy, the capacity is divided into onshore and offshore using (IRENA, 2025) data adapted to the study's perimeter, with their respective electricity production derived by calculating the 2023 Capacity Factors (CF) from IRENA and applying them to the 2024 capacity. This approach is used by the fact that IRENA had not yet provided specific production data for 2024 for either onshore or offshore wind or for solar PV at the time of the analysis. Consequently, the calculation for solar PV also utilized the 2023 CF derived from IRENA, multiplied by Ember's 2024 capacity, to define the total electricity production under the hypothesis that these factors remain constant.

The capacity factors are computed by applying the following formula (5.1) to the 2023 data sourced from (IRENA, 2025):

$$\text{Capacity Factor} = \frac{\text{Actual Energy Produced (MWh)}}{\text{Capacity Installed (MW)} * 8{,}760\ \text{h}} \quad (5.1)$$

The capacity factor computed for Wind Onshore is approximately 0.24, for Wind Offshore is approximately 0.32, while for Solar PV is approximately 0.12.

Finally, for the energy storage sector, the model distinguishes between power and energy dimensions: the installed capacity (power) for utility-scale batteries is sourced from (Energy Institute, 2025) while the energy storage capacity in PJ is derived from the (Solar Power Europe, 2025). This report identifies a total regional storage volume of 0.22 PJ, of which 33% is specifically attributed to utility-scale applications.

In Table 5.1 the Total Installed Capacity 2024 for the different technologies of the RES is reported. Table 5.2 represents the Total Installed Storage Capacity 2024 for battery, while Table 5.3 represents the Total Gross Electricity Production 2024 for the different technologies of the RES.

Table 5.1: Installed Capacity 2024

Technology	Installed Capacity 2024 [GW]
SCGT	75.98
COAL	152.02
OIL	29.50
CCGT	227.93
BIO	45.11
RESERVOIR	155.65
ROR	73.20
GEO	3.40
NUC	116.10
WIND ON	246.19
WINDOFF	35.67
PV	363.97
BATT	11.10
PHES	28.90

Table 5.2: Installed Storage Capacity 2024

Installed Storage Capacity [PJ]	2024
BATT	0.077

Table 5.3: Gross Electricity Production 2024

Technology	Gross Elec. Production 2024 [TWh]
SCGT	36.1
COAL	468.7
OIL	111.6
CCGT	674.0
BIO	201.5
ROR	298.9
RESERVOIR	381.5
GEO	24.2
NUC	779.0
WIND ON	519.2
WIND OFF	99.9
PV	384.9

5.1.2. Conversion from Gross to Net Electricity Generation

Following the accurate allocation of installed capacity and total gross electricity generation across the various technologies of the 2024 Reference Energy System (RES), the analysis proceeded to define the total net electricity production for each technology. This involved subtracting, for each technology, the specific share of energy produced for self-consumption (own use), sourced from (Sebastian Osorio, 2024), that is not delivered to the grid. For technologies where no 'own use' (self-consumption) value is reported in the Table 5.4, a null value has been assumed. This approach is consistent with the methodology adopted by (Sebastian Osorio, 2024), where internal auxiliary power consumption is treated as negligible for these specific energy units.

Table 5.4: Technology Own-Use

Technology	Own-Use
SCGT	3%
COAL	8%
OIL	9%
CCGT	3%
BIO	5%
RESERVOIR	2%
ROR	2%
NUC	5%

$$\text{Total Net Elec. Production [TWh]} = \text{Total Gross Elec. Production [TWh]} * (1 - \text{Own-Use}) \quad (5.2)$$

Equation 5.2 is used to compute the Total Net Electricity Production 2024 for the different technologies of the RES, as reported in Table 5.5.

By applying these adjustments, the 2024 baseline obtained represents the electricity that technologies produced and subsequently injected into the grid. This ensures that the model's starting point reflects the real-world net energy balance available for transmission and distribution and final consumption.

Table 5.5: Total Net Electricity Production 2024

Technology	Net Elec. Production 2024 [TWh]
WIND ON	519.15
WIND OFF	99.91
PV	384.89
RESERVOIR	374.03
BIO	191.90
ROR	293.06
GEO	24.20
NUC	741.95
SCGT	34.42
CCGT	654.37
COAL	434.01
OIL	102.41

5.1.3. Estimation of Transmission and Distribution (T&D) Losses

Following the definition of the total installed capacity and net electricity generation for each technology within the 2024 Reference Energy System (RES), the next step involves determining the 2024 losses associated to the transmission and distribution (T&D) infrastructure in the RES. This calculation is essential to derive the operational efficiency of the network layers represented in the model. Using the total aggregate electricity demand for the year 2024 for the European region, sourced from the IEA World Energy Outlook (WEO) 2025 (IEA, 2025), the total network losses are calculated as the difference between the sum of the net electricity production of all technologies in the RES and the final 2024 electricity demand.

Since self-consumption (own use) has already been subtracted in the previous section, this resulting delta represents the energy dissipated during transport and delivery to end-users. The total identified grid losses are then partitioned by allocating 25% to the Transmission network and 75% to the Distribution network. This 25/75 assumed repartition is justified by the inherent physical and structural differences between the two infrastructure levels:

- Voltage Levels and Resistance: Distribution networks operate at significantly lower voltages than transmission lines, which leads to higher currents for the same amount of power and, consequently, higher resistive ($I^2 R$) losses.
- Network Complexity: The distribution segment is characterized by a vastly greater total line length and a higher density of transformers (stepping down

to medium and low voltage), both of which contribute to higher cumulative technical losses compared to the streamlined, high-voltage transmission backbone.

Based on this allocation, the Transmission efficiency is obtained as one minus the ratio between the assigned transmission losses and the total net electricity production, resulting in a value of 98%. Similarly, the Distribution efficiency was computed, yielding a value of 93%. Table 5.6 reports the main numerical values used for the computation of the Transmission and Distribution efficiencies.

Table 5.6: Transmission and Distribution Efficiency Calculation

Net Production [TWh]	2024
SCGT	34.44
COAL	434.01
OIL	102.41
CCGT	654.37
BIO	191.90
ROR	293.06
RERSEVOIR	374.03
GEO	24.20
NUC	741.95
WIND ON	519.15
WIND OFF	99.91
PV	384.89
Total Net Elec. Production	3,854.31
Total Elec. Demand	3,487.00
Losses T&D	367.31
Losses Trasmission (25%)	91.83
Losses Distribution (75%)	275.48
Trasmission Efficiency	0.98
Distribution Efficiency	0.93

A key assumption within the model's technical parameters is that these efficiency values remain constant throughout the entire planning horizon (2024–2050). This implies that the percentage of energy lost during transmission and distribution does not fluctuate, allowing the model to focus on the structural changes in the generation mix and demand growth without accounting for potential future improvements in grid infrastructure efficiency.

The quantification of these specific efficiencies for the Transmission and Distribution network, alongside the isolation of self-consumption values, constituted a critical prerequisite for the model's calibration. This methodological step is essential to ensure the accurate integration of IEA WEO 2025 electricity demand projections as input parameters. By accounting for these factors, the model can correctly translate the IEA's projected final demand into the total generation requirements. According to the IEA WEO 2025 methodology, electricity demand is strictly defined as the residual of the following balance (IEA, 2025):

$$\text{Electricity Demand} = \text{Total Gross Generation} - \text{Own Use} - \text{T\&D losses} \quad (5.3)$$

5.2. 2024 Most Relevant Input Parameters for Model Calibration

The data obtained for the construction of the Reference Energy System (RES), including installed capacity, renewable capacity factors, and transmission and distribution (T&D) efficiencies, are subsequently integrated into the model and utilized as input parameters for the 2024 simulation.

The following step of the calibration phase consists in populating the model with all the necessary input parameters to perform a simulation restricted only to the year 2024. The specific objective of this run is to validate the model's accuracy by comparing its endogenous outputs against the previously reconstructed reference baseline in terms of net electricity production, as reported in Table 5.5.

For this calibration run, a strict constraint is imposed to prevent the installation of any new power generation capacity during the 2024 simulation year, ensuring that the results remained consistent with the established baseline. The only exception is made for investments in battery storage; this choice is dictated by their unique balancing function and the inherent difficulty of performing a precise calibration for storage systems in the absence of more granular, high-resolution comparative data. Furthermore, storage dynamics are heavily influenced by the model’s specific assumptions regarding temporal and spatial resolution, as well as the distribution of electricity demand across time slices.

Consequently, to ensure transparency in the calibration process, the following sections reports the primary inputs required specifically for this phase, including Availability Factor in Table 5.7, Capacity Factor (CF) in Table 5.9, Variable Cost in Table 5.10, Fuel Prices in Table 5.11, Emission Activity Ratio in Table 5.12,Emission Penalty (Carbon Tax) in Table 5.13, Specified Annual Demand in Table 5.14, Input Activity Ratio in Table 5.15, and Output Activity Ratio in Table 5.16, ensuring that the model’s starting point accurately reflects the real-world operational and economic conditions of the European power sector. It should be emphasized that while this section focuses on the key parameters essential for the calibration of the 2024 base year, the comprehensive list of all model inputs over the entire 2024–2050 planning horizon is presented in detail with all the assumption and sources within the dedicated chapter on Input Data.

Availability Factor

Table 5.7: Availability Factor 2024 for dispatchable technologies

Technology	Availability 2024
BIO	0.78
GEO	0.81
NUC	0.73
SCGT	0.78
CCGT	0.80
COAL	0.78
OIL	0.75

Table 5.8: Availability Factor 2024 for technologies constrained by capacity factor and batteries

Technology	Availability 2024
PHES	1.00
BATT	1.00
WIND ON	1.00
WIND OFF	1.00
PV	1.00
RESERVOIR	1.00
ROR	1.00

Capacity Factor

Table 5.9: Capacity Factor 2024

Technology	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Capacity factor	0.45	0.24	0.32	0.12	0.52

Variable Cost and Fuel Cost

Table 5.10: Variable Cost 2024

Technology	Variable Cost [$/MWh]
PHES	0.54
BATT	-
WIND ON	-
WIND OFF	-
PV	-
RESERVOIR	1.40
BIO	4.00
ROR	-
GEO	10.01
NUC	6.98
SCGT	5.00
CCGT	3.60
COAL	5.69
OIL	4.00

Table 5.11: Fuel Cost 2024

Fuel	Fuel Cost 2024 [$/MWh]
COAL	16.0
OIL	46.5
GAS	35.1
BIO	39.6
URN	9.0

Emission Penalty and Emission Activity Ratio

Table 5.12: Emission Activity Ratio 2024

Technology	Emission Activity Ratio 2024 [Ton/MWh]
COAL	0.823
OIL	0.717
CCGT	0.347
SCGT	0.521

Table 5.13: Emission Penalty 2024

Emission Penalty 2024 [$/Ton]
75.00

Specified Annual Demand

Table 5.14: Specified Annual Demand 2024

Commodity	Specified Annual Demand 2024 [TWh]
ELC_SERVICE	1,115.84
ELC_RES	1,011.23
ELC_IND	1,255.32
ELC_MOB	104.61
Aggregated Electricity	3,487.00

Input and Output Activity Ratio

Table 5.15: Input Activity Ratio 2024

Technology	Input Activity Ratio 2024
PHES	1.13
BATT	1.05
WIND ON	1.00
WIND OFF	1.00
PV	1.00
RESERVOIR	1.00
BIO	3.19
ROR	1.00
GEO	1.00
NUC	3.19
SCGT	2.58
CCGT	1.72
COAL	2.86
OIL	2.72
TRASMISSION	1.02
DISTRIBUTION	1.08

Table 5.16: Output Activity Ratio 2024

Technology	Output Activity Ratio 2024
PHES	0.89
BATT	0.95

5.3. Model Calibration

This section provides a detailed evaluation of the 2024 simulation outputs, focusing on Net Electricity Production. By comparing these initial results with the Net Electricity Production 2024 of the previously established European Reference Energy System (RES) baseline, specific discrepancies are identified and analysed.

These misalignments are attributed to several concurrent factors, ranging from the low availability and granularity of high-quality data to the inherent structural limitations of the modelling framework.

Based on this diagnostic assessment, a calibration strategy is implemented. This procedure aims to reduce the gap between simulation results and historical reality by fixing the model to a technically and historically grounded baseline. This ensures that the optimization pathways for subsequent years evolve from a validated 2024 starting point, providing a robust foundation for the entire long-term energy transition analysis.

5.3.1. Comparative Assessment: Model Output vs. European Reference Energy System

In the following section the output of the 2024 model simulation and the representative Reference Energy System are compared in terms of Total Net Electricity Production.

Figure 5.1 illustrates the graphical comparison between the 2024 net electricity production from the model simulation and the representative RES benchmark, while Table 5.17 provides the corresponding numerical values.

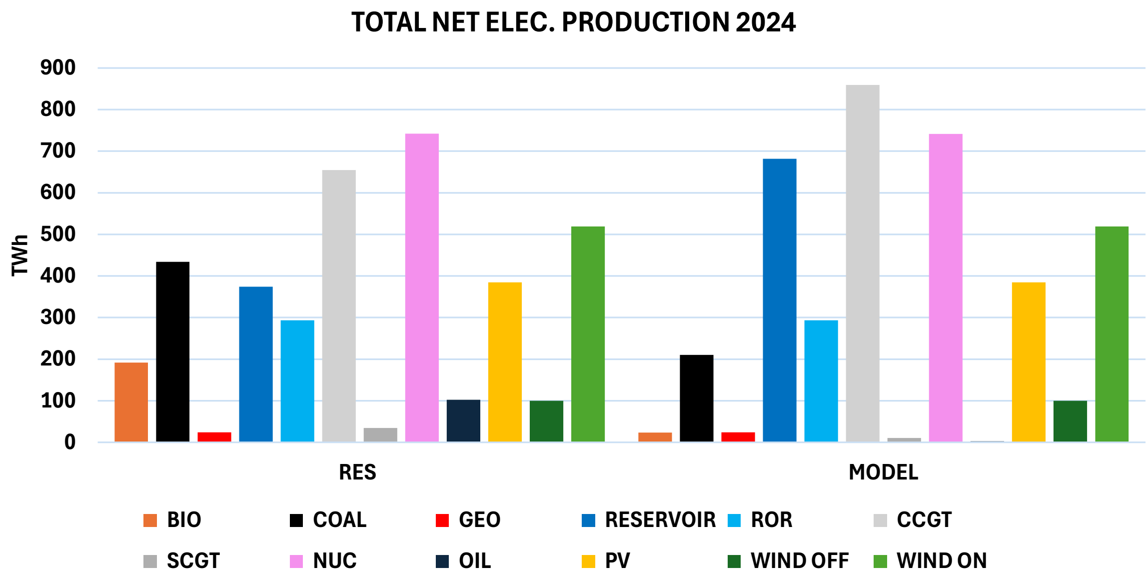

Figure 5.1: Comparison Total Net Electricity Production 2024

Table 5.17: Comparison Total Net Electricity Production 2024

Tot Net Elec. Production 2024 [TWh]	RES	MODEL
BIO	191.9	23.7
COAL	434.0	210.3
GEO	24.2	24.4
RESERVOIR	374.0	681.4
ROR	293.2	293.2
CCGT	654.4	859.4
SCGT	34.4	10.9
NUC	742.0	741.4
OIL	102.4	2.5
PV	384.9	384.9
WIND OFF	99.9	99.9
WIND ON	519.2	519.2

The analysis of the values and the technological comparison reveals that the 2024 simulation accurately captured the production levels of non-dispatchable renewable sources, such as Run-of-River, Onshore and Offshore Wind, and Solar PV. Furthermore, Nuclear power generation is also correctly represented. The primary discrepancies, however, are associated with other dispatchable technologies, specifically Coal, CCGT, SCGT, Oil, Biomass, and Hydro Reservoir.

The factors that led to these differences for biomass are linked to inherent model limitations as well as specific methodological assumptions and inputs. The primary reasons for these discrepancies include:

- Absence of the Thermal Sector and Combined Heat and Power (CHP): The model's exclusive focus on the power sector creates a significant difference from real-world operational logic, particularly regarding Combined Heat and Power (CHP). Because the model does not account for heat demand, the solver fails to recognize the economic advantage of biomass plants operating in cogeneration modes. The high bio-fuel costs of these plants are frequently offset by heat revenues. This is particularly critical for biomass: in the European Union, approximately 70% of electricity production from biomass is generated through cogeneration (European Commission, 2023). These biomass plants are typically co-located with industrial production sites, such as paper mills and sawmills, which require a near-constant supply of high-temperature heat. The thermal energy produced is utilized either within these industrial processes or by the biomass plants themselves to support their own operations. This heat utilization effectively compensates for the high costs of the biomass fuel and the associated operating expenses (OPEX). Not modelling this thermal demand and the resulting cost-offsetting benefits, the optimization applies an artificial penalty to biomass technologies, leading to a simulated production that is significantly lower than the historical 2024 reference.

- Economic Simplification and Policy Incentives: The model identifies the optimal mix exclusively through CAPEX, OPEX, and fuel costs. This logic ignores the complex stratification of subsidies, incentives, green or white certificates, and direct state investments that significantly alter the real-world competitiveness and dispatch priority of biomass (EMBER, 2024).

The model tends also to overestimate hydroelectric production if it is not properly constrained by an external parameter representing the actual limits of the natural resource.

Furthermore, the model fails to correctly represent the remaining production mix required to satisfy demand, which is distributed across four key technologies: CCGT, SCGT, Coal, and Oil.

This misalignment is not due to a single factor but rather a convergence of multiple concurrent reasons reflecting the nature and limits of the model, its high level of simplification, and the reality that the European power system must respond to various requirements beyond simple total cost minimization, such energy security and independence, as reported in (IEA, 2024).

These reasons include geographical and operational simplifications inherent in the model, economic and mathematical limitations inherent in the model and technical and temporal constraints, such as:

- "Copper Plate" Approach*:* Modelling the entirety of Continental Europe as a single region (RE1) assumes an infinitely capable electricity transmission grid. This ignores physical bottlenecks and Net Transfer Capacity (NTC) limits between different Member States, which dictate production differences and alter the dispatch order.
- Unified Demand Profile: The use of a single load profile (SpecifiedDemandProfile) for the entire continent flattens regional temporal and climatic differences, eliminating the need to manage non-simultaneous demand peaks across diverse geographical zones.
- Flattening of Resource Profiles: Aggregating resource profile for wind and solar into continental averages, by defining the average capacity factor, prevents the model from exploiting real geographic complementarities (e.g., wind in the North vs. sun in the South), thereby reducing the need for system flexibility and the activation of other dispatchable technologies.
- Disappearance of Local Reserve Requirements: Within a single-node model, the obligation to maintain specific shares of localized dispatchable

technologies to ensure grid stability (voltage and frequency) and system inertia disappears.

- "Winner-Takes-All" Logic: Linear programming tends to drive the solver toward the vertices of the feasible region. If one technology (e.g., gas) is even marginally more economical than another (e.g., coal), the model will fully saturate the former before activating the latter, resulting in extremely polarized generation mixes, as reported by (Schrattenholzer, 1991).
- Constant Fuel Costs: The assumption of invariant prices throughout the year eliminates energy market volatility. Daily price fluctuations allow for the coexistence of different sources through fuel-switching mechanisms. Furthermore, defining a single reference price for all Continental Europe is limiting; the reference cost used is based on (IEA, 2025) projections, specifically using the values provided for the EU.
- "Naked" Economic Competition: The model operates exclusively on CAPEX, OPEX, and fuel costs, ignoring the complex stratification of subsidies and state investments that significantly alter the real-world competitiveness of technologies.
- Absence of "System Adequacy" Constraints: The objective function minimizes only the TotalDiscountedCost, neglecting logic related to national security and energy sovereignty that leads governments to keep "firm" plants active even when they are not strictly economically optimal.
- Coal and Oil Penalty and Fuel Assumptions: Coal is significantly penalized within the model because the fuel cost is assumed to be that of Hard Coal, following the (IEA, 2025) assumptions. However, in the European reality, specifically in countries like Germany, Poland, Greece, Slovenia and the Czech Republic, lignite is still widely used (EUROSTAT, 2023). Lignite has significantly lower extraction and transport costs compared to hard coal, a factor the model does not account for in its current aggregate form. Furthermore, coal and oil are further penalized by the application of a Carbon Tax across the entire modelling region. This tax is assumed to be constant and equal to the average 2024 EU carbon price. The geographical perimeter of this study includes several non-EU countries, such as Türkiye and the Balkan nations, that do not currently enforce such stringent emission penalties and remain heavily dependent on these fossil fuels. By applying a high, uniform EU-standard carbon tax to the whole "Continental Europe" region, the model artificially reduces the economic competitiveness of coal and oil plants in those sub-regions, leading to an underestimation of their actual production compared to the 2024 reference data.
- Lack of Technical Flexibility Constraints: The absence of ramp-up/down limits and start-up/shut-down costs allows plants to vary production

instantaneously and at zero cost. This ignores the mechanical wear and thermal inertia of real plants, which in practice necessitates more continuous operation.

This phenomenon is particularly evident when analysing the 2024 production profiles by time slices (Figure 5.2, Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6, Figure 5.7), where technology utilization appears highly discontinuous. The model treats these assets as perfectly flexible units capable of freely modulating their power output at any moment. Conventional plants are typically operated at relatively constant load factors to maintain technical stability; any increase in power output is generally gradual and largely restricted to specific peak-shaving technologies, such as Open Cycle Gas Turbines (SCGT/GT). The omission of these physical constraints leads to unrealistic dispatch patterns at the time slice level, which consequently distorts the overall annual production figures.

- Unrealistic Technological Homogeneity: Aggregating plants into a few technological classes assumes that all European facilities have identical performance, ignoring efficiency differences related to age and site-specific engineering.
- Lack of Granularity in the Gas Sector: The absence of a clear distinction between Combined Cycle (CCGT) and Open Cycle (SCGT) turbines in some reporting prevents the model from correctly representing the trade-off between base-load efficiency and peaking flexibility.
- Perfect Foresight: The solver operates with total knowledge of future demand and weather conditions, eliminating the inefficiencies and safety reserves necessary in the real world to manage operational uncertainty.
- Storage Operational Data Scarcity: A lack of granular data on the actual use of batteries in 2024, combined with the physical constraint of "double dimensioning" (power vs. energy), leads the model to favour simpler programmable solutions over storage for mathematical ease.

5.3.2. The Calibration Phase: Synchronizing Model Dispatch with Empirical Data

Based on the analysis of the results presented in the previous section and the evaluation of the factors causing the discrepancies between the 2024 reference baseline and the simulation outputs, and in accordance with the cited reference documentation (Plazas-Niño F. B., 2025), the model is calibrating acting on two primary constraints: Total Technology Annual Activity Lower Limit [TWh] and Total Technology Annual Activity Upper Limit [TWh].

Specifically, for the hydro reservoir the electricity production has been exogenously limited to the reconstructed 2024 value with a constraint that serves to simulate the physical availability limits of the natural resource. Technically, this is achieved by setting the TotalAnnualTechnologyActivityUpperLimit for this technology in 2024 equal to the reconstructed production value of 374.03 TWh.

Regarding the remaining dispatchable technologies, specifically CCGT, SCGT, Coal, Bio and Oil, the reconstructed reference mix is reproduced in the model by introducing a TotalAnnualTechnologyActivityLowerLimit constraint set to the 2024 reference values, as reported in Table 5.18. The decision to implement these binding constraints is intended to overcome the modelling limitations and simplifications previously discussed.

Table 5.18: Total Technology Annual Activity Lower Limit 2024

Total Technology Annual Activity Lower Limit [TWh]	2024
BIO	191.9
SCGT	34.4
CCGT	654.4
COAL	434.0
OIL	102.4

Furthermore, this methodological approach is explicitly recommended by the reference documentation specific to this modelling interface, ensuring a robust and verified calibration of the simulation's start year.

5.3.3. 2024 Production Analysis by Time slices

Following the calibration of the model through the imposition of Total Technology Annual Activity Lower/Upper Limit constraints, a new simulation is performed to verify if these constraints allowed the model to accurately replicate the Renewable Energy Sources (RES) benchmark. The simulation yielded a positive outcome, successfully representing the annual production levels across the various technologies.

Furthermore, the objective value for the constrained 2024 simulation reached $ 179 billion, compared to $ 131 billion in the initial unconstrained run. This significant discrepancy highlights that, in the absence of constraints, the solver identified a more cost-optimal but historically unrealistic configuration for the 2024 production mix. The increase in the total system cost within the new simulation reflects the 'economic penalty' of aligning the model with actual historical data, effectively overriding the pure mathematical optimization that had initially favored a cheaper but technically inaccurate pathway.

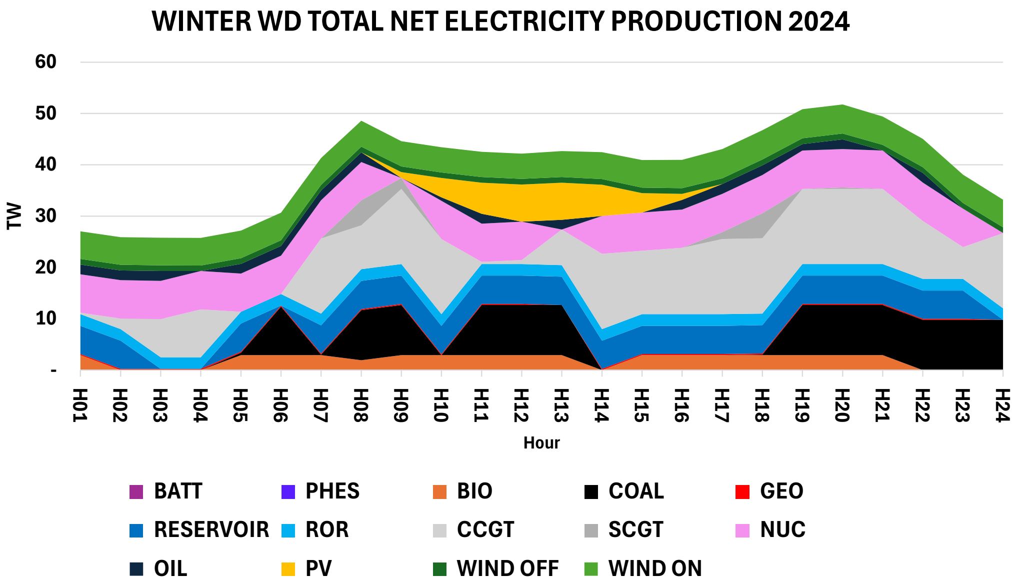

Figure 5.2: Winter Workday Total Net Electricity Production 2024

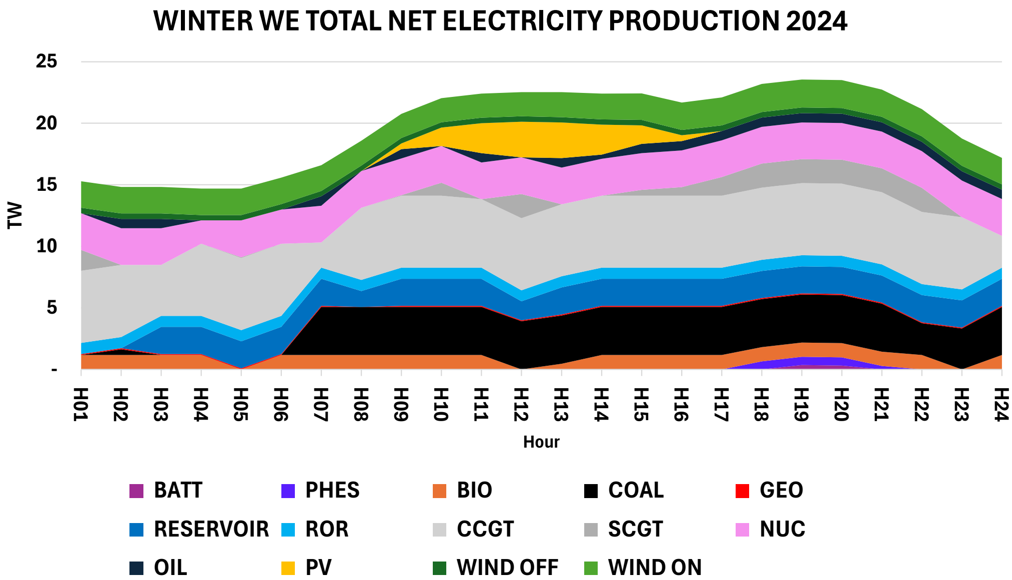

Figure 5.3: Winter Weekend Total Net Electricity Production 2024

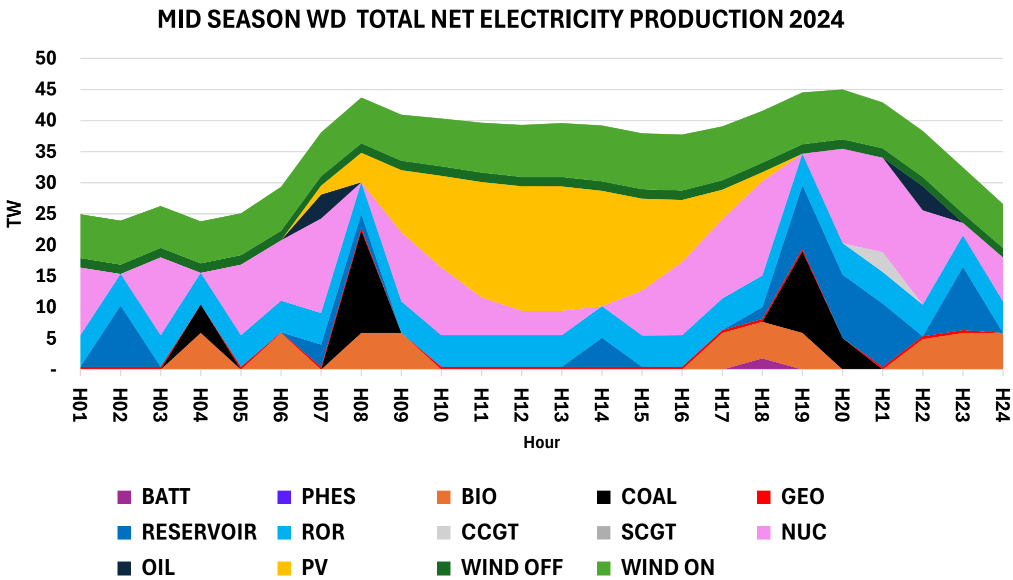

Figure 5.4: Mid-Season Workday Total Net Electricity Production 2024

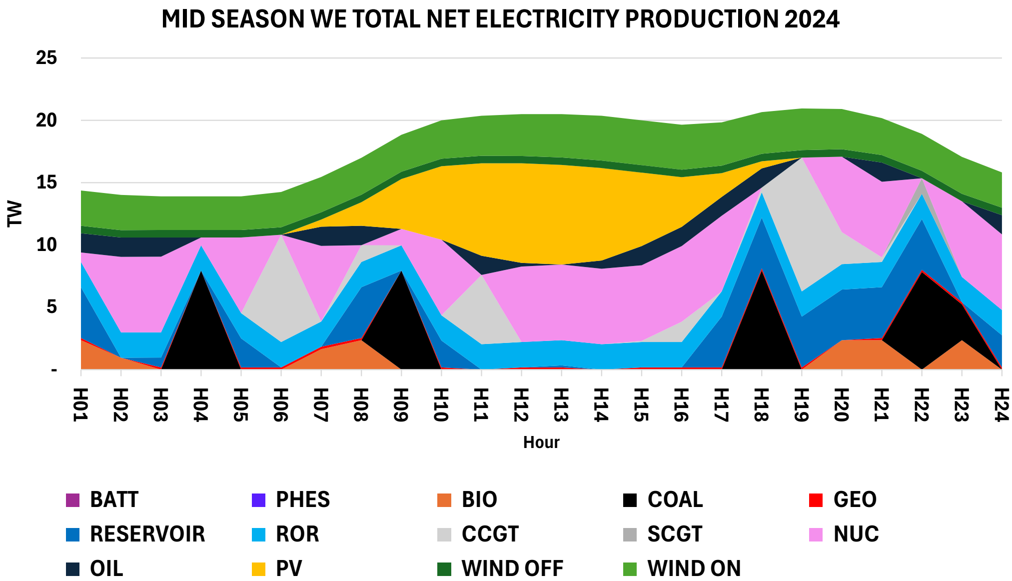

Figure 5.5: Mid-Season Weekend Total Net Electricity Production 2024

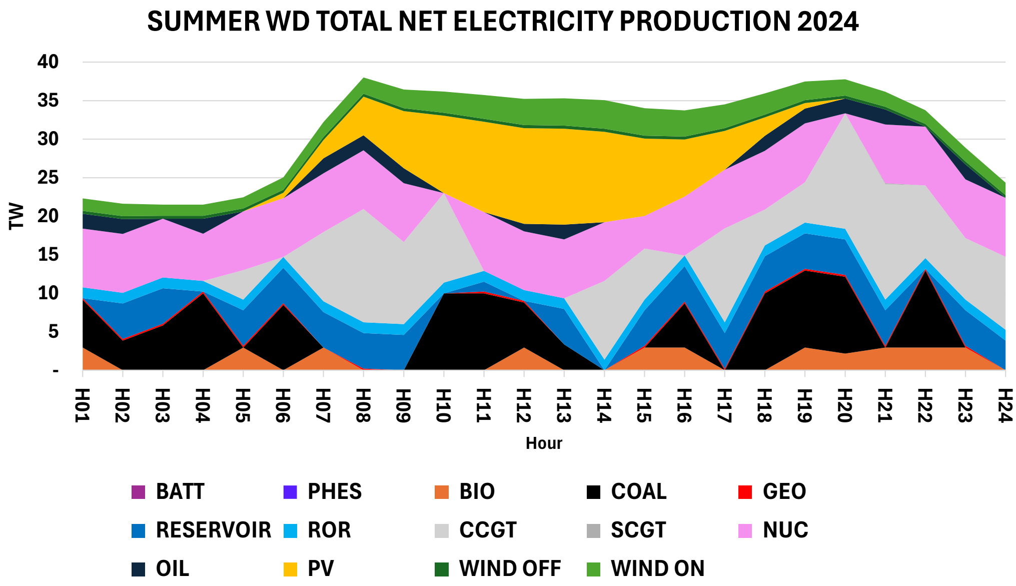

Figure 5.6: Summer Workday Total Net Electricity Production 2024

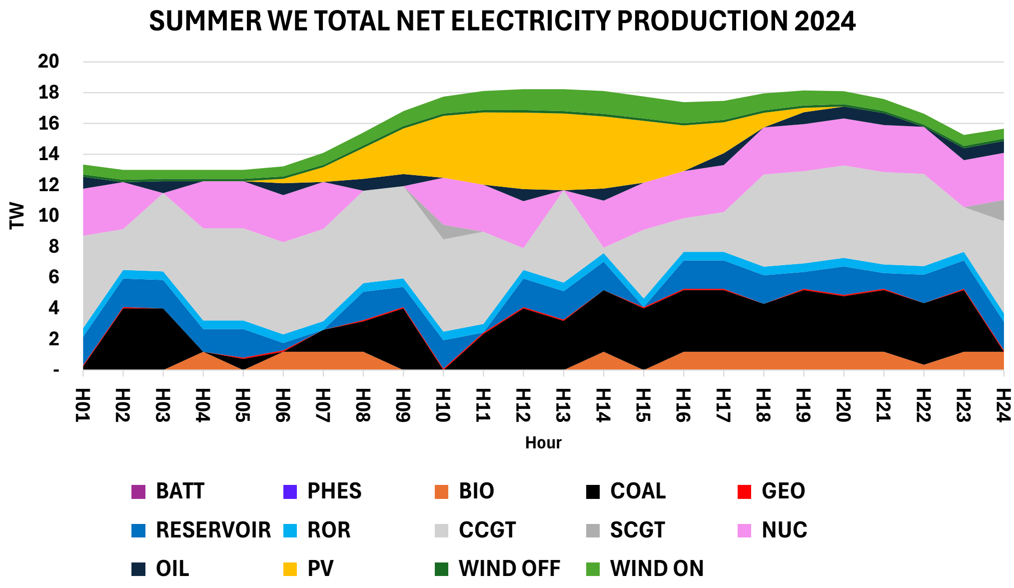

Figure 5.7: Summer Weekend Total Net Electricity Production 2024

The analysis of the 2024 production by time slice, reported for Winter in Figure 5.2 and Figure 5.3, for Midseason in Figure 5.4 and Figure 5.5 and for Summer in Figure 5.6 and Figure 5.7, confirms the solver's tendency to generate highly discontinuous solutions. The output for various firm technologies remains extremely variable from one time slice to the next; this is primarily due to the absence of ramping constraints and the simultaneous optimization of individual time slices. Under this framework, the model optimizes each block independently, based on Merit Order logic, without incentivizing gradual transitions between consecutive periods.

The analysis further reveals that variable renewables, such as Solar PV, Wind, and Run-of-river hydro, are dispatched continuously according to their specific Capacity Factors (CF), reflecting the underlying assumptions of zero marginal costs and an availability factor of 1. Similarly, nuclear, geothermal, and hydro reservoir technologies exhibit nearly continuous dispatch patterns while satisfying their respective availability constraints. In contrast, technologies such as biomass, CCGT, SCGT, coal, and oil are utilized mainly for peak management and in general for period of high electricity demand. This is particularly evident during the summer and winter seasons, when electricity demand peaks and renewable output is lower due to reduced natural resource availability.

Finally, the analysis confirms that the observed production peaks are primarily driven by the synergy between instantaneous electricity demand and battery charging cycles. Specifically, the production spike at 3 during mid-season workdays, Figure 5.4, is explicitly attributed to the storage replenishment phase, as the model optimizes energy availability for subsequent high-demand periods.

6 Input Parameters

This section provides a detailed overview of the inputs, assumptions, and sources used to define the model's parameters. To ensure clarity, a distinction is made between the common Input Parameters and Sets, which are shared across all three modelled scenarios, and the scenario-specific inputs that characterize the different pathways.

6.1. Common Scenario Modelling Inputs and Configuration

6.1.1. Model Configuration

Consistent with the methodological assumptions and the Reference Energy System (RES) described previously, the foundational sets, including technologies, storage systems, and commodities, have been integrated into the modelling interface. These elements determine the common structural base for all three simulated scenarios.

The technologies and commodities added to the interface correspond directly to those illustrated in the RES, Figure 4.1. A key distinction has been made regarding energy storage:

- Battery Storage: Configured as daily storage to manage short-term fluctuations and intra-day shifting.
- Pumped Hydro (PHS): Configured as yearly storage, reflecting its capacity for large-scale energy balancing across longer time horizons.

To ensure consistency across the model, the following units of measurement are defined in the model Interface:

- Energy and Activity: Measured in Petajoules (PJ).
- Capacity: Measured in Gigawatts (GW).
- Emissions: Carbon dioxide (CO_2) is defined as the sole emission agent, with emissive technologies appropriately flagged within the interface to track environmental impact, measured in Mton.
- Storage Linkage: The interface requires a specific definition linking the energy capacity component (PJ) of storage with its associated power unit (GW) to maintain physical consistency.

- Activity/Commodity Mapping: For every technology, the interface specifies the input and output commodities (e.g., Natural Gas as input and Electricity as output).

The simulation covers a modelling period from 2024 to 2050. To accurately capture the variability of both renewable generation and electricity demand, the temporal resolution is structured into 144 discrete time slices, derived from the following parameters:

- 3 Seasons: Winter, Summer, and Mid-season.
- 2 Day-types: Workday and Weekend.
- 24 Daily time-steps: Representing each hour of the day.

Each of the 144 time slices is uniquely defined by its specific combination of season, day-type, and hour. The simulation time horizon (2024–2050), the number of seasons, day-types, daily time-steps, and their sequence are entered into the interface. Subsequently, the 144 time slices are defined, specifying the season, day, and daily time step to which each one belongs.

Finally, the interface configuration is completed by defining the base currency ($) (for cost optimization) and the number of modes of operation for the various technologies. The number of modes of operation is set to 2 due to the presence of storage technologies that require one mode of operation for the charging phase and another for the discharging phase. All the other technologies operate only in mode 1.

6.1.2. Common Modelling Input

Following the definition of the structural sets and the temporal resolution, this section details the common modelling inputs shared across all three scenarios. These parameters establish the techno-economic and environmental framework within which optimization occurs.

Discount Rate

In the context of energy systems modelling, the discount rate represents the time preference rate used to discount future cash flows into their present value. This core economic principle recognizes that a dollar received in the future is worth less than a dollar received today due to factors such as opportunity costs and inherent risks. Consequently, to accurately compare costs and benefits occurring at different points in time across the 2024–2050 horizon, all future expenditures must be adjusted to their present value.

The selection of this rate significantly influences the model's optimization behaviour. A higher discount rate indicates a higher opportunity cost or a higher required return, which diminishes the present value of future cash flows. In such a scenario, the model tends to favour technologies with lower upfront capital expenditures (CAPEX), even if they incur higher future operating costs (OPEX). Conversely, a lower discount rate increases the present value of future cash flows, making capital-intensive technologies, more economically attractive within the optimization logic.

For the purposes of this study, a discount rate of 5% (0.05) has been applied . This value reflects the relevant time preference and opportunity cost of capital for a continental energy system. It is utilized as the default standard value suggested by the modelling interface and aligns with common academic and social energy planning practices, providing a balanced approach between short-term cost-saving and long-term infrastructure investment (Diego Garcia Gusano, 2016), (Monika Foltyn-Zarychta, 2021). It is important to emphasize that this value is constant for the entire simulation period (2024–2050), ensuring uniform economic consistency across all phases of the modelled energy transition. In addition, this discount rate is applied to each technology and storage component since in the MUIO interface is not possible to assign different discount rate to different technologies.

Capacity to Activity Unit

The CapacityToActivityUnit parameter is essential for defining the mathematical relationship between a technology's installed capacity and the total energy activity it can perform over a specific period. It represents the maximum annual activity achievable if one unit of capacity operates at full load for an entire year. This parameter acts as a conversion factor that converts the units of power and energy. In this model, where capacity is measured in Gigawatts (GW) and energy activity is measured in Petajoules (PJ), the parameter specifies how many Petajoules a single Gigawatt of capacity can generate annually (PJ/GW).

The value is calculated based on the number of seconds in a year (365 days*24 hours*3600 seconds = 31,536,000 seconds). Consequently, for all power generation technologies (power plants), a value of 31.54 PJ/GW is applied. This reflects the physical reality that 1 GW of capacity operating continuously for one-year results in approximately 31.54 PJ of energy output. In contrast, for infrastructure and accounting components such as natural resources, demand nodes, and Transmission & Distribution (T&D) technologies, a value of 1 PJ/GW is utilized. The CapacityToActivityUnit is defined as time-independent for each technology, providing a stable ratio that rules the relationship between investment in capacity and the resulting energy potential across the entire simulation period.

Operational Life

Table 6.1: Operational Life

Technology	Operational Life [Years]
COAL CCS	35
GAS CCS	30
PHES	50
BATT	15
WIND ON	25
WIND OFF	30
PV	30
RESERVOIR	50
BIO	30
ROR	50
GEO	30
NUC	60
SCGT	25
CCGT	30
COAL	35
OIL	25

The OperationalLife parameter defines the technical lifespan of each technology or system integrated into the model. It represents the fixed number of years a technology can remain active and productive before it reaches the end of its utility and must be decommissioned or replaced by new capacity. Within the modeling framework, this parameter is treated as time-independent for each specific technology and is expressed as a discrete value in years.

In the optimization logic, the operational life is a critical parameter for determining the retirement schedule of installed capacity. When a technology reaches the end of its specified life, the model must decide whether to reinvest in new capacity to meet demand, considering the updated techno-economic conditions of that future year. This parameter also influences the period over which capital costs are distributed, directly affecting the long-term investment strategies and the evolution of the energy mix throughout the 2024–2050 simulation period. By accurately defining the lifespan of various assets, ranging from shorter-lived technologies like batteries to long-term infrastructure like hydroelectric plants or nuclear reactors, the model ensures a realistic representation of the natural turnover and modernization of the European power fleet. Table 6.1 represents the OperationalLife considered for the different technologies.

The operational life for Coal CCS, Gas CCS, Wind Off, Pv, Coal and CCGT are sourced from (LAZARD, 2025), for Geothermal, Nuclear, Reservoir, Run-Of-River and Pumped Hydro are sourced from (Working Group III Technical Support Unit

IPCC, 2014), for Biomass, Wind On, SCGT and Oil are sourced from (Timilsina, 2020) and finally for Battery the operational life is sourced from (NREL, 2024).

Year Split

Table 6.2: Year Split

TimeSlice	Year Split
Winter_WD	0.176136
Winter_WE	0.070440
Summer_WD	0.180024
Summer_WE	0.072000
MidSeason_WD	0.358104
MidSeason_WE	0.143256

The Year Split parameter is used to define the specific duration of each time-slice, representing the sub-annual time increments within the model. It is a time-dependent parameter expressed as a fraction of the total year for each time-slice; therefore, each individual value ranges between 0 and 1. Specifically, the Year Split of a time-slice is calculated as the ratio of the number of hours represented by that slice divided by the 8,760 total hours of a calendar year.

The summation of all Year Split values over a single year must equal 1 (subject to minor rounding adjustments), ensuring that the total annual duration is mathematically accounted for. The calculation of this fraction depends on the seasonal, day-type and daily durations defined in the model. For this study, the year is subdivided as follows:

- Summer: 3 months (representing 25% of the year).
- Winter: 3 months (representing 25% of the year).
- Mid-season: 6 months (representing 50% of the year).

The year split of a single hour within a specific day-type (Workday or Weekend) and season, is computed as the ratio between the total number of hours that specific "type" of time occurs during the year and the total number of hours in a year (8,760h). Table 6.2 reports the Year Split value for each representative day-type for each season. The YearSplit value for each of the 24 hourly time slices within every season and day-type corresponds to 1/24th of the respective aggregate value provided in Table 6.2.

Day Split

The Day Split parameter is used to define the duration of an individual occurrence of each time-slice within the model. Unlike the Year Split, which weights the total annual duration of a time-slice, the Day Split is specifically utilized to govern the temporal behaviour of energy storage systems. It is a time-dependent parameter expressed as a fraction of the total year, with values ranging between 0 and 1.

The primary function of this parameter is to ensure that the storage logic correctly accounts for the rate of charge and discharge within a representative day. In this study, since each representative day-type is divided into 24 discrete hourly brackets, the duration of each individual hour relative to the entire year is uniform.

Consequently, for every hourly time-slice across all seasons and day-types, the Day Split value is calculated as the ratio of one hour to the total hours in a year:

$$DaySplit = \frac{1}{8760} \cong 0.000114155 \quad (6.1)$$

This value is applied consistently to all 24 daily time brackets.

Days in Day Type

The DaysInDayType parameter is used to specify the number of sequential days contained within a single occurrence of a specific day-type. This parameter is crucial for scaling the model's daily time brackets to represent a full week accurately, ensuring that the total energy consumption and production over a year are correctly accounted for within the seasonal blocks.

In this modelling framework, the temporal resolution distinguishes between workdays and weekends to capture the distinct load patterns and demand behaviours associated with each. Consequently, the parameter values are assigned as follows:

- Workday: Set to 5, representing the standard five-day working week (Monday through Friday).
- Weekend: Set to 2, representing the two-day weekend period (Saturday and Sunday).

By defining these values, the model correctly weights the 24-hour profiles of each day-type.

Availability Factor

Table 6.3: Availability Factor for dispatchable technologies

Availability	2024	2025	2026-2027	2028-2050
COAL CCS	0.85	0.85	0.85	0.85
GAS CCS	0.90	0.90	0.90	0.90
BIO	0.78	0.78	0.78	0.78
GEO	0.81	0.81	0.81	0.81
NUC	0.73	0.75	0.80	0.85
SCGT	0.78	0.78	0.78	0.78
CCGT	0.80	0.80	0.80	0.80
COAL	0.78	0.78	0.78	0.78
OIL	0.75	0.75	0.75	0.75

Table 6.4: Availability Factor for technologies subject to Capacity Factor constraints and batteries

Availability	2024-2050
PHES	1.00
BATT	1.00
WIND ON	1.00
WIND OFF	1.00
PV	1.00
RESERVOIR	1.00
ROR	1.00

The AvailabilityFactor parameter defines the maximum proportion of time a technology can be operational throughout the year, expressed as a fraction ranging from 0 to 1. In energy systems modelling, this parameter is critical for reflecting real-world operational constraints that prevent a power plant from running at 100% capacity for all 8,760 hours of the year.

The primary purpose of the Availability Factor is to account for:

- Planned Outages: Scheduled periods for routine maintenance, safety inspections, and technical upgrades.
- Unscheduled Outages: Forced shutdowns due to mechanical failures or unexpected technical issues.

By setting this factor, the model is forced to recognize that a portion of the installed capacity will be unavailable for dispatch.

In the model, this parameter is typically defined for each technology and can be adjusted over the simulation period. Table 6.3 represents the different Availability Factor considered for dispatchable technologies.

For renewable technologies, specifically Solar PV, Onshore and Offshore Wind, and Run-of-River (RoR) hydro and Reservoir, the Availability Factor is set to 1, as in Table 6.4. This methodological choice is made because the output of these technologies is already constrained by time-dependent Capacity Factor profiles. Since these profiles are derived from empirical production data that inherently incorporate both resource variability and technical downtime, setting the Availability Factor to 1 prevents 'double counting' of production constraints. Batteries and pumped hydro are assigned an availability factor of 1 due to their high operational reliability and the fact that maintenance can typically be scheduled during periods of low demand without affecting overall system capacity.

Furthermore, it is important to emphasize that a gradual increase in the annual availability factor for nuclear power has been assumed over the modeling horizon. This trajectory is intended to reflect a potential recovery in operational performance, accounting for improvements in fleet maintenance, the resolution of historical technical issues, and the enhanced reliability of the European nuclear fleet over time.

The Availability Factor (AF) for established technologies, including Coal, Oil, SCGT, CCGT, and Biomass, is sourced from (Sebastian Osorio, 2024). For Nuclear and Geothermal assets, the AF is empirically calculated as the ratio between actual net production and maximum theoretical output based on 2024 installed capacity.

A distinct approach is adopted for Carbon Capture and Storage (CCS) technologies (Gas CCS and Coal CCS). Since these units are modeled as new installations built exclusively from 2025 onwards, they are assigned higher availability factors of 0.90 and 0.85, respectively. This assumption is predicated on the fact that state-of-the-art plants benefit from superior component reliability and optimized maintenance schedules compared to the aging legacy fleet. The validity of these parameters is supported by the concept of inherent availability, which accounts solely for unplanned failures. According to (Savsar, 2015), the inherent availability for modern power cycles is estimated at 0.97–0.98; therefore, the selected operational values (0.90 and 0.85) are considered realistic as they allow for a maintenance window that is significantly shorter than that of conventional, older plants.

Consistent with the technical complexities of solid fuel handling, Coal CCS maintains a lower level of availability compared to its gas counterpart. This accounts for the unavoidable mechanical stress and auxiliary system requirements, such as fuel pulverization and ash processing, which, even in new installations, inherently increase the probability of both scheduled and unscheduled downtime relative to gas-fired units.

Residual Capacity

Table 6.5: Residual Capacity

Residual Capacity [GW]	2024	2025	2030	2035	2040	2045	2050
SCGT	75.98	75.15	65.41	44.02	19.63	5.19	0.76
COAL	152.02	147.78	94.81	25.13	1.94	0.04	0.00
OIL	29.50	29.18	25.40	17.09	7.62	2.02	0.30
CCGT	227.93	227.85	224.83	201.77	132.07	48.30	8.19
BIO	45.11	45.11	45.08	44.67	42.10	33.72	19.57
RESERVOIR	155.65	155.65	155.65	155.65	155.65	155.65	155.65
ROR	73.25	73.25	73.25	73.25	73.25	73.25	73.25
GEO	3.40	3.40	3.40	3.40	3.40	3.40	3.40
NUC	116.10	116.10	116.01	114.96	108.35	86.79	50.37
WIND ON	246.19	246.19	246.19	246.05	240.59	190.40	75.96
WINDOFF	35.67	35.67	35.67	35.67	35.67	35.53	30.01
PV	363.97	363.96	363.79	362.13	352.46	317.92	242.37
BATT	11.00	11.00	10.95	7.98	0.89	0.00	0.00
PHES	28.90	28.90	28.90	28.90	28.90	28.90	28.90

The ResidualCapacity parameter represents the capacity installed prior to the modelling period and specifies the existing capital stock available in the base year. While the specific calculation for the 2024 residual capacity is detailed in Cap. 5, the following section outlines the expected decommissioning profile for this installed capacity from 2024 to 2050.

For specific assets such as Hydroelectric, Pumped Hydro and Geothermal, the model assumes that capacity remains constant throughout the simulation interval. This assumption reflects the nature of these large-scale civil engineering projects, which are typically maintained through continuous refurbishments rather than total decommissioning. For all other technologies, a gradual retirement profile is applied using a stochastic approach based on a Survivor Curve. This methodology assumes that the retirement of power plants follows an Inverse Cumulative Normal Distribution, centred on the technology's expected maximum mean lifetime (μ) and modulated by a standard deviation (σ).The algorithm calculates, for each simulation year, the conditional probability that an asset survives to year y, given that it has already survived to its current age. This produces a decommissioning profile shaped like an "Inverse S", highlighting three main parts:

- Stability Phase (Plateau): Very few retirements occur early in the plant's life.
- Acceleration Phase: Retirements peak as the fleet reaches its mean expected lifetime.
- Final Tail: A gradual phase-out of the few remaining, exceptionally long-lived plants.

The standard deviation (σ) for the survivor curves defines the temporal dispersion of capacity decommissioning relative to the mean technical lifetime (μ) of each asset class. These parameters are calibrated to reflect both the physical reliability of the technologies and strategic technoeconomic considerations within the model and are reported in Table 6.6.

A notably high standard deviation of 7.0 is assigned to Solar PV. This parameterization is specifically chosen to model a possible real-world trend where existing installations are replaced by newer, higher-efficiency modules instead of waiting for the physical end-of-life. Given the sharp CAPEX reductions assumed across all scenarios, the model utilizes this broader distribution to simulate economic obsolescence and technological repowering. Consequently, the decommissioning process for PV is more dynamic, prioritizing the integration of cost-effective new capacity over the continued operation of aging assets, with an optimum repowering time for PV plants that is between 15 and 21 years, as reported in (Sina Herceg, 2022).

Regarding flexible and thermal technologies, the σ values account for operational and sector heterogeneity:

- SCGT and Oil-fired plants are assigned a higher value of 6.0. These technologies serve as "peakers," and their retirement remains highly sensitive to the penetration of cheaper alternatives, such as storage, and to evolving environmental regulations. This leads to a wider and more uncertain decommissioning window compared to baseload plants.
- Biomass is also assigned a σ of 6.0. This value accounts for the heterogeneity of the sector, where plant survival depends heavily on localized fuel supply chains and potential conversions to other fuel types, creating a less uniform retirement age compared to standard gas plants.
- Nuclear power utilizes a σ of 6.0 to account for the uncertainty surrounding long-term life extensions and the complex regulatory landscape.
- CCGT units are assigned a value of 5.0, representing a more standardized retirement profile for mid-merit thermal assets.

In contrast, Wind (Onshore and Offshore) and Coal technologies are characterized by a lower σ of 4.0. For wind assets, decommissioning is more strictly governed by mechanical fatigue and lease expirations, resulting in a more concentrated retirement window. For coal, the parameter reflects rigid phase-out schedules often dictated by environmental policy. Finally, Battery Storage is assigned to the lowest value (2.5), as electrochemical degradation follows a highly predictable technical trajectory, leaving minimal margin for strategic decommissioning variance.

To determine the expected residual capacity for each simulation year, it is necessary to estimate the average age of the European power plant fleet as of 2024. These values, detailed in Table 6.6, serve as the starting point for the decommissioning trajectories.

The average age of the European existing fleet in 2024 is derived through a comprehensive analysis of historical installation trends and sector-specific literature:

- Solar PV, Onshore Wind, Offshore Wind, and Biomass: The average age is estimated by analysing historical installed capacity curves for Europe provided by (EMBER, 2025), cross-referenced with the standard operational life of each technology, reported in Table 6.1.
- Nuclear: Estimates for the nuclear fleet are based on (Francisco Javier Farfan Orozco, 2016).
- Fossil Fuels (Coal, Gas, and Oil): The average age for the thermal fleet is derived from specific power plant databases. Specifically for Coal (Global Energy Monitor, 2026) and for Oil and Gas (Global Energy Monitor, 2026).
- Battery: The average age is estimated by analysing historical installed capacity curves for Europe provided by (Energy Institute, 2025) cross-referenced with the standard operational life of the storage, reported in Table 6.13.

The residual capacity for each technology in any given year y is calculated using the following mathematical framework:

$$Cap(y) = Cap_{2024} * \frac{1-\Phi(Age_{2024}+(y-2024);\mu;\sigma)}{1-\Phi(Age_{2024};\mu;\sigma)} \quad (6.2)$$

Where:

- Cap_{2024}: The initial capacity installed in the base year (2024).
- $\Phi(x, \mu, \sigma)$: The Cumulative Distribution Function (CDF) of a Normal Distribution.
- Age_{2024}**:** The estimated average age of the technology's fleet already in existence by 2024.
- $(y - 2024)$**:** The elapsed time from the start of the simulation to the target year y.

Table 6.6: Parameters for the Survivor Curve

Technology	Avarage Age [years]	Maximum Life [years]	σ	Capacity 2024 [GW]
SCGT	23.00	35.00	6.00	75.98
COAL	38.00	45.00	4.00	152.02
OIL	23.00	35.00	6.00	29.50
CCGT	18.00	35.00	5.00	227.93
BIO	15.00	40.00	6.00	45.11
NUC	35.00	60.00	6.00	116.10
WIND ON	11.00	35.00	4.00	246.19
WIND OFF	6.00	35.00	4.00	35.67
PV	6.00	35.00	7.00	363.97
BATT	2.50	15.00	2.50	11.00

In Table 6.5 the computed Residual Capacity for the different technologies, computed applying the Survivor Curve to the initial 2024 stock is reported.

Variable cost

Table 6.7: Variable Cost

Variable Cost [$/MWh]	2024	2025	2030	2035	2040	2045	2050
COAL CCS	7.31	7.27	7.09	6.95	6.84	6.80	6.77
GAS CCS	5.76	5.72	5.62	5.54	5.44	5.44	5.40
PHES	0.54	0.54	0.54	0.54	0.54	0.54	0.54
BATT	-	-	-	-	-	-	-
WIND ON	-	-	-	-	-	-	-
WIND OFF	-	-	-	-	-	-	-
PV	-	-	-	-	-	-	-
RESERVOIR	1.40	1.40	1.40	1.40	1.40	1.40	1.40
BIO	4.00	4.00	4.00	4.00	4.00	4.00	4.00
ROR	-	-	-	-	-	-	-
GEO	10.01	10.01	10.01	10.01	10.01	10.01	10.01
NUC	6.98	6.98	6.98	6.98	6.98	6.98	6.98
SCGT	5.00	5.00	5.00	5.00	5.00	5.00	5.00
CCGT	3.60	3.60	3.60	3.60	3.60	3.60	3.60
COAL	5.69	5.69	5.69	5.69	5.69	5.69	5.69
OIL	4.00	4.00	4.00	4.00	4.00	4.00	4.00

The Variable Cost parameter represents the expenses incurred during the actual operation of a technology, scaling directly with its activity. Unlike fixed costs, which are paid regardless of usage, variable costs are only triggered when the plant is generating energy.

For non-dispatchable renewable technologies, specifically Solar PV, Onshore Wind, Offshore Wind, and Run-of-River (RoR) hydro, the variable operating costs have been set to zero. This assumption reflects the absence of fuel costs and the fact that maintenance expenses directly attributable to generation are considered negligible for these sources.

Similarly, battery storage systems have also been modeled with zero variable costs. In this case, it is assumed that operational expenses are entirely covered within the fixed O&M costs, and the primary "cost" of operation is represented by efficiency losses during charge and discharge cycles, which are handled separately in the technology's technical specifications.

Table 6.7 reports the variable cost assumed and used for the different technologies.

The variable cost for both the CCS technologies is sourced from (L. Hatton, 2024), for Biomass and Nuclear is sourced from (Fraunhofer ISE, 2024), for SCGT and Coal is sourced from (LAZARD, 2025), for Pumped Hydro from (NREL , 2024), for Oil from (Danish Energy Agency, 2016), for Geothermal from (Working Group III Technical Support Unit IPCC, 2014), for CCGT is the mean value between (LAZARD, 2025) and (Triconomics (EU Commission), 2020) and for Reservoir is sourced from (Timilsina, 2020). A progressive reduction in variable costs is assumed exclusively for CCS technologies, as reported in (L. Hatton, 2024), reflecting their status as emerging technologies.

Input Activity Ratio

Table 6.8: Input Activity Ratio

Input Activity Ratio	2024	2025	2030	2035	2040	2045	2050
COAL CCS	2.94	2.92	2.85	2.79	2.79	2.79	2.79
GAS CCS	1.98	1.98	1.94	1.91	1.91	1.91	1.91
PHES	1.13	1.13	1.13	1.13	1.13	1.13	1.13
BATT	1.05	1.05	1.05	1.05	1.05	1.05	1.05
WIND ON	1.00	1.00	1.00	1.00	1.00	1.00	1.00
WIND OFF	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PV	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RESERVOIR	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BIO	3.19	3.14	2.92	2.92	2.92	2.92	2.92
ROR	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GEO	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NUC	3.19	3.19	3.19	3.19	3.19	3.19	3.19
SCGT	2.58	2.56	2.46	2.46	2.46	2.46	2.46
CCGT	1.72	1.71	1.69	1.68	1.67	1.66	1.66
COAL	2.86	2.86	2.86	2.86	2.86	2.86	2.86
OIL	2.72	2.70	2.59	2.59	2.59	2.59	2.59
TRASMISSION	1.02	1.02	1.02	1.02	1.02	1.02	1.02
DISTRIBUTION	1.08	1.08	1.08	1.08	1.08	1.08	1.08

Table 6.9: Gross Efficiency

Gross Efficiency	2024	2025	2030	2035	2040	2045	2050
CCGT	0.60	0.60	0.61	0.61	0.62	0.62	0.62
SCGT	0.40	0.40	0.42	0.42	0.42	0.42	0.42
BIO	0.33	0.34	0.36	0.36	0.36	0.36	0.36
OIL	0.40	0.40	0.42	0.42	0.42	0.42	0.42
GAS CCS	0.52	0.52	0.53	0.54	0.54	0.54	0.54
COAL CCS	0.37	0.37	0.38	0.39	0.39	0.39	0.39
COAL	0.38	0.38	0.38	0.38	0.38	0.38	0.38
NUC	0.33	0.33	0.33	0.33	0.33	0.33	0.33
TRASMISSION	0.98	0.98	0.98	0.98	0.98	0.98	0.98
DISTRIBUTION	0.93	0.93	0.93	0.93	0.93	0.93	0.93
BATT (Round-Trip)	0.90	0.90	0.90	0.90	0.90	0.90	0.90
PHES (Round-Trip)	0.80	0.80	0.80	0.80	0.80	0.80	0.80
BATT (One-way-Efficiency)	0.95	0.95	0.95	0.95	0.95	0.95	0.95
PHES (One -way-Efficiency)	0.89	0.89	0.89	0.89	0.89	0.89	0.89

Table 6.10: Net Efficiency

Net Efficiency	2024	2025	2030	2035	2040	2045	2050
CCGT	0.58	0.58	0.59	0.59	0.60	0.60	0.60
SCGT	0.39	0.39	0.41	0.41	0.41	0.41	0.41
BIO	0.31	0.32	0.34	0.34	0.34	0.34	0.34
OIL	0.37	0.37	0.39	0.39	0.39	0.39	0.39
GAS CCS	0.50	0.51	0.51	0.52	0.52	0.52	0.52
COAL CCS	0.34	0.34	0.35	0.36	0.36	0.36	0.36
COAL	0.35	0.35	0.35	0.35	0.35	0.35	0.35
NUC	0.31	0.31	0.31	0.31	0.31	0.31	0.31

Table 6.11: Technology Own-Use

Technology	Own-Use
SCGT	3%
COAL	8%
OIL	9%
CCGT	3%
BIO	5%
RESERVOIR	2%
ROR	2%
NUC	5%
GAS CCS	3%
COAL CCS	8%

The InputActivityRatio parameter is used to define the quantity of input required to sustain the activity of a specific technology. Specifically, it indicates how many units of input (such as fuel or primary energy) are needed for each unit of output activity produced. For all technologies considered in this study, the InputActivityRatio is defined and applied to Mode of Operation 1.

This parameter is mathematically defined as the reciprocal of the net energy efficiency:

$$InputActivityRatio = \frac{1}{\eta_{net}} \ (6.3)$$

$$\eta_{net} = \eta_{gross} * (1 - \%OwnUse) \ (6.4)$$

It is fundamental to note that the calculation of the Input Activity Ratio, reported in equation 6.3, is based on net efficiency (Table 6.10). This is obtained by starting from the gross efficiency (Table 6.9) and subtracting the "self-consumption" required for the plant's internal operations (Table 6.11), as reported in equation 6.4.

This approach ensures that the model accurately reflects the energy available to the system, net of the auxiliary losses necessary for the generation. For CCS-equipped technologies, the auxiliary power consumption (own use) is assumed to be identical to that of their conventional counterparts. This is justified by the fact that the gross efficiency parameters for CCS plants are already downwardly adjusted to internalize the energy penalty associated with the carbon capture process (IEA, 2025). Therefore, the additional energy required for sequestration is already reflected in the reduced efficiency rather than in an increased 'own use' coefficient.

In cases where internal plant consumption is assumed to be zero, the InputActivityRatio is calculated as $1/\eta_{gross}$. In addition, it is important to underline that for storage the InputActivityRatio is defined as $1/\eta_{one-way-efficiency}$.

The modelling of the InputActivityRatio parameter varies depending on the maturity and expected technological progress of the different sources:

- Constant Efficiency: For most technologies, the InputActivityRatio (Table 6.8) is assumed to remain constant throughout the modelling horizon, reflecting stable performance for mature or standard assets.
- Technological Improvement: For specific technologies, a progressive reduction in the InputActivityRatio (Table 6.8), and thus a corresponding increase in efficiency, is modelled. This trend applies to SCGT, CCGT, Oil-fired plants, Biomass, and Carbon Capture and Storage (CCS) systems (both Gas CCS and Coal CCS). These improvements are aligned with the technological learning curves and performance projections outlined in (IEA, 2025), starting from the 2024 assumed value.

By incorporating these dynamic ratios, the model captures the long-term impact of technical innovation on fuel consumption and operational costs across the 2024–2050 simulation period.

The 2024 gross efficiency for: Coal, SCGT, CCGT and Biomass is sourced from (Fraunhofer ISE, 2024), the gross efficiency for Nuclear is sourced from

(Triconomics (EU Commission), 2020) and (IEA, NEA, OECD, 2020), for Gas CCS and Coal CCS from (IEA, 2025), for Oil from (Danish Energy Agency, 2016). The Round Trip efficiency for Pumped Hydro is sourced from (NREL , 2024) and for Battery from (LAZARD, 2021).

Output Activity Ratio

Table 6.12: Output Activity Ratio

Output Activity Ratio	2024-2050
PHES	0.89
BATT	0.95

The OutputActivityRatio parameter defines the amount of output generated per unit of activity for a given technology. It effectively establishes the relationship between the internal activity of the system and the final commodity delivered to the energy mix.

For most technologies in this study, the OutputActivityRatio is set to 1 for Mode of Operation 1. This is because the technical conversion losses, representing the difference between the primary energy input and the final energy output, have already been accounted for in the InputActivityRatio through the reciprocal of the net efficiency. Consequently, one unit of internal activity corresponds exactly to one unit of output commodity produced.

A distinct modelling approach is required for Storage systems to correctly represent their operational losses. Unlike standard generation technologies, batteries involve two distinct modes of operation:

- Mode of Operation 1 (Charging): The process of taking energy from the grid and storing it.
- Mode of Operation 2 (Discharging): The process of releasing stored energy back to the grid.

For batteries, an OutputActivityRatio is specifically defined for Mode of Operation 2 and this is set equal to the One-Way-Efficiency. This is done to accurately reflect the round-trip efficiency of the system. While the charging phase incurs losses, the discharging phase also experiences electrical and thermal losses. By setting an OutputActivityRatio (Table 6.12) of less than 1 for Mode 2, the model accounts for the energy dissipated during the discharge cycle, ensuring that the total energy recovered is physically consistent with the performance of modern electrochemical storage units.

Operational Life of Storage

Table 6.13: Operational Life of Storage

Storage Technology	BATT	PHES
Operationa Life [Years]	15.00	50.00

The OperationalLifeStorage parameter defines the technical and economic lifespan of storage technologies within the model. It represents the fixed number of years a storage asset can remain operational before it reaches the end of its service life and must be decommissioned or replaced. Like the operational life of generation technologies, this parameter is treated as time-independent for each specific storage type and is expressed as a discrete value in years.

- Batteries: Typically have a shorter operational life (e.g., 10–15 years) due to chemical degradation from charge and discharge cycles, the operational life for Battery Storage is sourced in (NREL, 2024) and reported in Table 6.13.
- Pumped Hydro: These assets are modeled with significantly longer lifespans, reflecting their nature as long-term infrastructure projects with durable civil engineering components. The Operational Life for Pumped Hydro Storage is sourced in (Working Group III Technical Support Unit IPCC, 2014) and reported in Table 6.13.

Storage Level Start

The StorageLevelStart parameter is used to define the initial energy state of a storage system at the very beginning of the first modelling period. This parameter ensures that the model has a clear starting point for calculating energy balances and storage trajectories over time. The value is expressed as a fraction of the system's maximum storage capacity, ranging from 0 to 1. For this study, a default value of 0.5 (50%) has been assigned to the battery storage systems.

Setting the starting level at 50% allows the model the flexibility to either discharge energy immediately to meet early demand or continue charging if surplus renewable generation is available, avoiding the constraints of a completely empty or completely full system at the simulation's onset.

Residual Storage Capacity

Table 6.14: Residual Storage Capacity

Residual Storage Capacity [PJ]	2024	2025	2030	2035	2040	2045	2050
BATT	0.077	0.08	0.08	0.06	0.01	-	-

The ResidualStorageCapacity parameter represents the storage capacity installed prior to the beginning of the model period (2024). It is used to specify the existing capital stock available in the base year, ensuring the model accounts for the energy storage assets already integrated into the European grid. Following the same logic applied to power generation capacity, the existing storage stock is not retired abruptly. Instead, it follows a stochastic decommissioning profile governed by the Survivor Curve (based on the Inverse Cumulative Normal Distribution), ruled by the same parameters defined for the Battery power component. This ensures a gradual reduction of the initial 2024 capacity over time, reflecting the varying ages and physical degradation of the existing fleet, as reported in Table 6.14.

The modelling of the 2024 capacity for the two primary storage technologies modelled is defined as follows:

- Battery Storage: The residual storage capacity for utility scale batteries in 2024 is estimated at 0.077 PJ, approximately 33% of the total installed storage capacity for that year, that is approximately 0.22 PJ (or 61.1 GWh), as sourced in (Solar Power Europe, 2025). This reflects the assumption that utility-scale batteries, the primary focus of this grid-level model, account for roughly one-third of the total European battery fleet, with the remainder composed of smaller-scale or behind-the-meter applications, as sourced in (Solar Power Europe, 2025).
- Pumped Hydro Storage (PHS): Due to a lack of granular historical data specifically regarding storage energy capacity (MWh) versus power capacity (MW), and assuming that the primary economic burden lies in the civil engineering and structural components, the model adopts a distinct approach for PHS. The residual storage capacity is set to zero, allowing the optimization solver to define the necessary storage volume based on the structural constraints and power capacity established in the model. This approach avoids assigning arbitrary storage costs to existing large-scale infrastructure while ensuring system adequacy.

Technology To and From Storage

The TechnologyToStorage and TechnologyFromStorage parameters are dimensionless "tags" used to establish the logical links between energy generation/conversion technologies and storage systems. They define the direction of energy flow, allowing the model to distinguish between components that "charge" the storage and those that "discharge" it.

The TechnologyToStorage parameter identifies technologies that provide energy input to a specific storage asset. It is set to 1 when a physical or logical link exists (allowing the technology to charge the storage) and 0 when there is no link. In this model, this tag is applied to the "charging" mode 1 of the battery system, connecting the power conversion component to the energy storage reservoir.

Similarly, TechnologyFromStorage parameter identifies technologies that receive energy output from a storage asset. It is set to 1 to indicate that the technology can draw energy from the storage and 0 otherwise. This is used for the "discharging" mode 2 of the battery system, connecting the power conversion component to the energy storage capacity.

In this specific framework, the link between the battery power component (the inverter/converter) and the storage component (the energy reservoir) is made explicit. By decoupling power and energy in this way, the model can independently optimize the power capacity (how fast the battery can charge/discharge) and the energy capacity (how much total energy it can hold), providing a more granular representation of battery performance and degradation.

Specified Demand Profile

Table 6.15: Winter Workdays Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
Winter_WD_H01	0.0083	0.0065	0.0068	0.0010
Winter_WD_H02	0.0081	0.0057	0.0068	0.0010
Winter_WD_H03	0.0080	0.0057	0.0068	0.0010
Winter_WD_H04	0.0080	0.0057	0.0068	0.0010
Winter_WD_H05	0.0084	0.0065	0.0068	0.0013
Winter_WD_H06	0.0096	0.0081	0.0068	0.0031
Winter_WD_H07	0.0117	0.0130	0.0077	0.0083
Winter_WD_H08	0.0134	0.0162	0.0087	0.0167
Winter_WD_H09	0.0142	0.0113	0.0087	0.0209
Winter_WD_H10	0.0146	0.0097	0.0087	0.0219
Winter_WD_H11	0.0146	0.0089	0.0087	0.0219
Winter_WD_H12	0.0144	0.0089	0.0087	0.0209
Winter_WD_H13	0.0142	0.0097	0.0087	0.0198
Winter_WD_H14	0.0141	0.0097	0.0087	0.0188
Winter_WD_H15	0.0138	0.0089	0.0087	0.0167
Winter_WD_H16	0.0134	0.0097	0.0087	0.0136
Winter_WD_H17	0.0124	0.0130	0.0087	0.0104
Winter_WD_H18	0.0114	0.0177	0.0087	0.0073
Winter_WD_H19	0.0105	0.0226	0.0087	0.0052
Winter_WD_H20	0.0099	0.0242	0.0087	0.0042
Winter_WD_H21	0.0094	0.0226	0.0087	0.0031
Winter_WD_H22	0.0091	0.0193	0.0087	0.0021
Winter_WD_H23	0.0088	0.0146	0.0077	0.0017
Winter_WD_H24	0.0085	0.0097	0.0068	0.0013

Table 6.16: Winter Weekends Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
Winter_WE_H01	0.0031	0.0029	0.0058	0.0010
Winter_WE_H02	0.0030	0.0026	0.0058	0.0010
Winter_WE_H03	0.0030	0.0026	0.0058	0.0010
Winter_WE_H04	0.0029	0.0026	0.0058	0.0010
Winter_WE_H05	0.0029	0.0026	0.0058	0.0010
Winter_WE_H06	0.0030	0.0029	0.0058	0.0010
Winter_WE_H07	0.0032	0.0039	0.0058	0.0017
Winter_WE_H08	0.0035	0.0052	0.0058	0.0031
Winter_WE_H09	0.0038	0.0065	0.0058	0.0063
Winter_WE_H10	0.0040	0.0071	0.0058	0.0094
Winter_WE_H11	0.0041	0.0071	0.0058	0.0115
Winter_WE_H12	0.0041	0.0071	0.0058	0.0125
Winter_WE_H13	0.0041	0.0071	0.0058	0.0125
Winter_WE_H14	0.0041	0.0071	0.0058	0.0115
Winter_WE_H15	0.0040	0.0071	0.0058	0.0094
Winter_WE_H16	0.0039	0.0071	0.0058	0.0073
Winter_WE_H17	0.0038	0.0078	0.0058	0.0052
Winter_WE_H18	0.0037	0.0091	0.0058	0.0038
Winter_WE_H19	0.0036	0.0097	0.0058	0.0025
Winter_WE_H20	0.0036	0.0097	0.0058	0.0021
Winter_WE_H21	0.0035	0.0091	0.0058	0.0017
Winter_WE_H22	0.0034	0.0078	0.0058	0.0013
Winter_WE_H23	0.0033	0.0058	0.0058	0.0010
Winter_WE_H24	0.0032	0.0045	0.0058	0.0010

Table 6.17: Summer Workdays Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
Summer_WD_H01	0.0072	0.0035	0.0068	0.0010
Summer_WD_H02	0.0070	0.0031	0.0068	0.0010
Summer_WD_H03	0.0069	0.0031	0.0068	0.0010
Summer_WD_H04	0.0069	0.0031	0.0068	0.0010
Summer_WD_H05	0.0073	0.0035	0.0068	0.0013
Summer_WD_H06	0.0084	0.0044	0.0068	0.0031
Summer_WD_H07	0.0103	0.0070	0.0077	0.0083
Summer_WD_H08	0.0116	0.0087	0.0087	0.0167
Summer_WD_H09	0.0123	0.0061	0.0087	0.0209
Summer_WD_H10	0.0128	0.0052	0.0087	0.0219
Summer_WD_H11	0.0128	0.0048	0.0087	0.0219
Summer_WD_H12	0.0125	0.0048	0.0087	0.0209
Summer_WD_H13	0.0123	0.0052	0.0087	0.0198
Summer_WD_H14	0.0122	0.0052	0.0087	0.0188
Summer_WD_H15	0.0119	0.0048	0.0087	0.0167
Summer_WD_H16	0.0116	0.0052	0.0087	0.0136
Summer_WD_H17	0.0109	0.0070	0.0087	0.0104
Summer_WD_H18	0.0100	0.0096	0.0087	0.0073
Summer_WD_H19	0.0091	0.0122	0.0087	0.0052
Summer_WD_H20	0.0086	0.0131	0.0087	0.0042
Summer_WD_H21	0.0082	0.0122	0.0087	0.0031
Summer_WD_H22	0.0079	0.0105	0.0087	0.0021
Summer_WD_H23	0.0075	0.0078	0.0077	0.0017
Summer_WD_H24	0.0073	0.0052	0.0068	0.0013

Table 6.18: Summer Weekends Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
Summer_WE_H01	0.0027	0.0016	0.0058	0.0010
Summer_WE_H02	0.0026	0.0014	0.0058	0.0010
Summer_WE_H03	0.0026	0.0014	0.0058	0.0010
Summer_WE_H04	0.0026	0.0014	0.0058	0.0010
Summer_WE_H05	0.0026	0.0014	0.0058	0.0010
Summer_WE_H06	0.0026	0.0016	0.0058	0.0010
Summer_WE_H07	0.0028	0.0021	0.0058	0.0017
Summer_WE_H08	0.0031	0.0028	0.0058	0.0031
Summer_WE_H09	0.0033	0.0035	0.0058	0.0063
Summer_WE_H10	0.0035	0.0038	0.0058	0.0094
Summer_WE_H11	0.0036	0.0038	0.0058	0.0115
Summer_WE_H12	0.0036	0.0038	0.0058	0.0125
Summer_WE_H13	0.0036	0.0038	0.0058	0.0125
Summer_WE_H14	0.0036	0.0038	0.0058	0.0115
Summer_WE_H15	0.0035	0.0038	0.0058	0.0094
Summer_WE_H16	0.0034	0.0038	0.0058	0.0073
Summer_WE_H17	0.0033	0.0042	0.0058	0.0052
Summer_WE_H18	0.0032	0.0049	0.0058	0.0038
Summer_WE_H19	0.0032	0.0052	0.0058	0.0025
Summer_WE_H20	0.0032	0.0052	0.0058	0.0021
Summer_WE_H21	0.0031	0.0049	0.0058	0.0017
Summer_WE_H22	0.0030	0.0042	0.0058	0.0013
Summer_WE_H23	0.0029	0.0031	0.0058	0.0010
Summer_WE_H24	0.0028	0.0024	0.0068	0.0010

Table 6.19: Mid-Season Workdays Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
MidSeason_WD_H01	0.0080	0.0050	0.0068	0.0010
MidSeason_WD_H02	0.0077	0.0044	0.0068	0.0010
MidSeason_WD_H03	0.0076	0.0044	0.0068	0.0010
MidSeason_WD_H04	0.0076	0.0044	0.0068	0.0010
MidSeason_WD_H05	0.0081	0.0050	0.0068	0.0013
MidSeason_WD_H06	0.0092	0.0062	0.0077	0.0031
MidSeason_WD_H07	0.0113	0.0100	0.0087	0.0083
MidSeason_WD_H08	0.0128	0.0125	0.0087	0.0167
MidSeason_WD_H09	0.0136	0.0087	0.0087	0.0209
MidSeason_WD_H10	0.0141	0.0075	0.0087	0.0219
MidSeason_WD_H11	0.0141	0.0069	0.0087	0.0219
MidSeason_WD_H12	0.0139	0.0069	0.0087	0.0209
MidSeason_WD_H13	0.0137	0.0075	0.0087	0.0198
MidSeason_WD_H14	0.0135	0.0075	0.0087	0.0188
MidSeason_WD_H15	0.0132	0.0069	0.0087	0.0167
MidSeason_WD_H16	0.0128	0.0075	0.0087	0.0136
MidSeason_WD_H17	0.0119	0.0100	0.0087	0.0104
MidSeason_WD_H18	0.0110	0.0137	0.0087	0.0073
MidSeason_WD_H19	0.0101	0.0174	0.0087	0.0052
MidSeason_WD_H20	0.0095	0.0186	0.0087	0.0042
MidSeason_WD_H21	0.0090	0.0174	0.0087	0.0031
MidSeason_WD_H22	0.0087	0.0149	0.0077	0.0021
MidSeason_WD_H23	0.0084	0.0112	0.0068	0.0017
MidSeason_WD_H24	0.0081	0.0075	0.0058	0.0013

Table 6.20: Mid-Season Weekends Specified Demand Profile

Specified Demand Profile	ELC_SER	ELC_RES	ELC_IND	ELC_MOB
MidSeason_WE_H01	0.0030	0.0022	0.0058	0.0010
MidSeason_WE_H02	0.0029	0.0020	0.0058	0.0010
MidSeason_WE_H03	0.0028	0.0020	0.0058	0.0010
MidSeason_WE_H04	0.0028	0.0020	0.0058	0.0010
MidSeason_WE_H05	0.0028	0.0020	0.0058	0.0010
MidSeason_WE_H06	0.0029	0.0022	0.0058	0.0010
MidSeason_WE_H07	0.0031	0.0030	0.0058	0.0017
MidSeason_WE_H08	0.0033	0.0040	0.0058	0.0031
MidSeason_WE_H09	0.0036	0.0050	0.0058	0.0063
MidSeason_WE_H10	0.0038	0.0055	0.0058	0.0094
MidSeason_WE_H11	0.0039	0.0055	0.0058	0.0115
MidSeason_WE_H12	0.0039	0.0055	0.0058	0.0125
MidSeason_WE_H13	0.0039	0.0055	0.0058	0.0125
MidSeason_WE_H14	0.0039	0.0055	0.0058	0.0115
MidSeason_WE_H15	0.0038	0.0055	0.0058	0.0094
MidSeason_WE_H16	0.0037	0.0055	0.0058	0.0073
MidSeason_WE_H17	0.0036	0.0060	0.0058	0.0052
MidSeason_WE_H18	0.0035	0.0070	0.0058	0.0038
MidSeason_WE_H19	0.0034	0.0075	0.0058	0.0025
MidSeason_WE_H20	0.0034	0.0075	0.0058	0.0021
MidSeason_WE_H21	0.0033	0.0070	0.0058	0.0017
MidSeason_WE_H22	0.0032	0.0060	0.0059	0.0013
MidSeason_WE_H23	0.0031	0.0045	0.0058	0.0010
MidSeason_WE_H24	0.0030	0.0035	0.0058	0.0010

The SpecifiedDemandProfile is a fundamental parameter used to define the temporal variation of energy requirements throughout the year. This input allows for the detailed definition of the demand profile, ensuring that the model accounts for the timing of energy consumption rather than just the total magnitude.

The parameter sets the share of annual demand occurring in each specific time-slice, expressed as a fraction between 0 and 1. The summation of all values in the Specified Demand Profile over a single year must equal exactly 1 (allowing for negligible rounding errors). This profile must be paired with the Specified Annual Demand parameter, which determines the total magnitude of demand for that year.

While total electricity demand varies across different analysed scenarios due to the disaggregation into four specific sectors, the demand profile is assumed to remain constant across every scenario.

The profiles for different sectors and time-slices have been defined to remain consistent with historical European load profiles:

- ELC_RES: The residential load profile (ELC_RES) is characterized by a multi-layered temporal variability that reflects both the effects of climatic conditions and anthropogenic habits. On a diurnal scale, the demand follows a distinct bi-modal distribution. After reaching an absolute minimum during the early morning hours (03:00–04:00), the load experiences its first significant increase, the morning peak (07:00–08:00), driven by the start of daily activities. This is followed by a relative midday plateau before ending in a sharp, primary evening peak between 19:00 and 21:00, triggered by the simultaneous use of lighting, appliances, and space conditioning as residents return home. This daily cycle is further modulated by a weekly pattern where consumption is non-uniform; empirical data indicates a higher energy share during the weekends, with Sunday representing the peak of the week due to increased domestic presence. Seasonally, the profile exhibits strong cyclicality: the highest demand is concentrated in winter (December and January) to satisfy thermal and lighting requirements, reaching its minimum in June, with a secondary, moderate increase in the summer months linked to cooling loads (NATCONSUMERS, 2016).

- ELC_IND: The industrial load profile (ELC_IND) is characterized by high structural stability and a near-total absence of seasonal fluctuations, reflecting the rigid planning of production shifts and process-driven energy requirements. Industrial demand is modelled as independent of climatic variables, with identical values across Winter, Summer, and Midseason, indicating that thermal or lighting variations have negligible impact on its total energy balance. The temporal distribution relies heavily on the Weekday (WD) versus Weekend (WE) distinction, weekend levels represent only essential maintenance or continuous-cycle baseloads. On a diurnal scale, the profile exhibits an exceptionally flat "baseload" behaviour, as factory consumption remains remarkably constant across early, late, and night shifts during production periods (Patrick Dehning, 2019).
- ELC_SERVICE: The service and commercial sector load profile (ELC_SERVICE) exhibits a distinct hybrid nature that reflects a high dependency on business operating hours and climatic conditions, distinguishing it from both the residential and industrial sectors. On a diurnal scale, the weekday profile is characterized by a steep morning ramp between 07:00 and 09:00, culminating in a broad high-consumption plateau maintained consistently throughout the working day before declining in the late afternoon. The weekly distribution reveals a notable reduction in demand during the weekends; however, a substantial residual load remains, higher than that of the industrial sector, due to essential continuous-cycle operations such as hospitals, security systems, data centres, and commercial refrigeration. Seasonally, the sector shows pronounced variability:

consumption peaks are reached in winter (December and January) for space heating and again in summer (July and August) for cooling and ventilation, while the mid-season months exhibit the lowest values due to reduced thermal stress on commercial buildings (Frits Møller Andersen, 2024).

- ELC_MOB: The electric mobility load profile (ELC_MOB) is primarily driven by vehicle usage cycles and charging infrastructure accessibility, exhibiting distinct temporal behaviours between workdays and weekends. On workdays (Wd), the profile shows a pronounced morning ramp-up starting around 09:00 AM, coinciding with people arriving at their workplaces and initiating charging sessions, whereas weekend profiles (Sa/Su) exhibit significantly lower morning demand with activities starting later and remaining more concentrated in the afternoon. Despite these differences, all days culminate in a primary evening peak between 16:00 and 22:00, representing the convergence of late-day workplace charging and the beginning of residential charging as vehicles return home (Christopher Hecht, 2023).

Specifically, the modelling captures:

- Seasonal Variability: Fluctuations in demand across the three modelled seasons.
- Sector-Specific Behaviour: The unique consumption signatures of the four analysed sectors.
- Day-Type Variation: The distinct energy usage patterns observed between workdays and weekends.

In practice, the demand profile for each sector in every time-slice is qualitatively reconstructed to follow and reflect real-world historical load profiles, providing a realistic representation of European power system stress throughout the 2024–2050 period. Table 6.15, Table 6.16, Table 6.17, Table 6.18, Table 6.19 and Table 6.20 reports the specified demand profile for the 4 electricity demand sector across the different time slices of Winter, Summer and Midseason workdays and weekends.

Emission Activity Ratio

Table 6.21: Emission Activity Ratio

Emission Activity Ratio [Ton/MWh]	2024	2025	2030	2035	2040	2045	2050
COAL CCS	0.102	0.101	0.099	0.096	0.080	0.064	0.048
GAS CCS	0.040	0.040	0.039	0.039	0.032	0.026	0.019
COAL	0.823	0.823	0.823	0.823	0.823	0.823	0.823
OIL	0.717	0.711	0.683	0.683	0.683	0.683	0.683
CCGT	0.347	0.346	0.341	0.339	0.338	0.336	0.336
SCGT	0.521	0.516	0.496	0.496	0.496	0.496	0.496

Table 6.22: Fuel Emission Factor

Fuel	Natural gas	Coal	Oil
Fuel Emission Factor (Kton/PJ)	56.10	96.10	73.30

The EmissionActivityRatio is used to set the specific emission factor for each technology. It defines the relationship between the activity of a technology and its environmental impact, indicating how many units of emissions are released for every unit of energy activity produced.

This parameter is technology and emission-specific and is applied to all emissive technologies in the model, specifically: Coal, Oil, CCGT, SCGT, Gas CCS (CCG+CCS), and Coal CCS.

The value of the Emission Activity Ratio for each technology is calculated as the ratio between the fuel emission factor, reported in Table 6.22 and sourced from (IPCC, 2006) and the net efficiency of the technology, reported in Table 6.10:

$$EmissionActivityRatio\ \left({}^{Kton\ CO_2}/_{PJ}\right) = \frac{FuelEmissionFactor_{IPCC}\ \left({}^{Kton\ CO_2}/_{PJ}\right)}{\eta_{net}} \quad (6.5)$$

This approach ensures that as plant efficiency increases over time (as described in the Input Activity Ratio section), the emissions per unit of output activity decrease accordingly.

For technologies equipped with carbon capture, the Emission Activity Ratio is reduced by a percentage corresponding to the plant's CO_2 capture rate. The model assumes a progressive improvement in capture technology:

- Until 2035: A capture rate of 90% is assumed for both Gas and Coal CCS plants.
- From 2035 onwards: The capture rate increases to 95%, reflecting technological advancements in carbon sequestration.

Table 6.20 reports the computed values of Emission Activity Ratio for the different emissive technologies.

The parameter serves as the basis for calculating the total carbon footprint of the energy system. When the Emission Activity Ratio is multiplied by the total activity of each emissive technology, the model provides the total Mton of CO_2 emitted:

$$Total\ Emission\ (Mton\ CO_2) = \ EmissionActivityRatio\ *\ TechnologyActivity \quad (6.6)$$

This calculation is fundamental for the model to evaluate the impact of the Carbon Tax and to ensure compliance with the decarbonization targets set within the different simulation scenarios.

Capacity Factor

Table 6.23: Winter Workdays Capacity Factor

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Winter_WD_H01	0.48	0.31	0.48	-	0.55
Winter_WD_H02	0.48	0.31	0.48	-	0.55
Winter_WD_H03	0.48	0.31	0.48	-	0.55
Winter_WD_H04	0.48	0.32	0.48	-	0.55
Winter_WD_H05	0.48	0.33	0.48	-	0.55
Winter_WD_H06	0.48	0.34	0.48	-	0.55
Winter_WD_H07	0.48	0.34	0.48	-	0.55
Winter_WD_H08	0.48	0.34	0.48	-	0.55
Winter_WD_H09	0.48	0.34	0.48	0.05	0.55
Winter_WD_H10	0.48	0.35	0.48	0.16	0.55
Winter_WD_H11	0.48	0.35	0.48	0.26	0.55
Winter_WD_H12	0.48	0.36	0.48	0.31	0.55
Winter_WD_H13	0.48	0.36	0.48	0.31	0.55
Winter_WD_H14	0.48	0.36	0.48	0.26	0.55
Winter_WD_H15	0.48	0.36	0.48	0.16	0.55
Winter_WD_H16	0.48	0.35	0.48	0.05	0.55
Winter_WD_H17	0.48	0.35	0.49	-	0.55
Winter_WD_H18	0.48	0.34	0.49	-	0.55
Winter_WD_H19	0.48	0.34	0.49	-	0.55
Winter_WD_H20	0.48	0.34	0.49	-	0.55
Winter_WD_H21	0.48	0.34	0.48	-	0.55
Winter_WD_H22	0.48	0.33	0.48	-	0.55
Winter_WD_H23	0.48	0.32	0.48	-	0.55
Winter_WD_H24	0.48	0.31	0.48	-	0.55

Table 6.24: Winter Weekends Capacity Factor

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Winter_WE_H01	0.48	0.31	0.48	-	0.55
Winter_WE_H02	0.48	0.31	0.48	-	0.55
Winter_WE_H03	0.48	0.31	0.48	-	0.55
Winter_WE_H04	0.48	0.32	0.48	-	0.55
Winter_WE_H05	0.48	0.33	0.48	-	0.55
Winter_WE_H06	0.48	0.34	0.48	-	0.55
Winter_WE_H07	0.48	0.34	0.48	-	0.55
Winter_WE_H08	0.48	0.34	0.48	-	0.55
Winter_WE_H09	0.48	0.34	0.48	0.05	0.55
Winter_WE_H10	0.48	0.35	0.48	0.16	0.55
Winter_WE_H11	0.48	0.35	0.48	0.26	0.55
Winter_WE_H12	0.48	0.36	0.48	0.31	0.55
Winter_WE_H13	0.48	0.36	0.48	0.31	0.55
Winter_WE_H14	0.48	0.36	0.48	0.26	0.55
Winter_WE_H15	0.48	0.36	0.48	0.16	0.55
Winter_WE_H16	0.48	0.35	0.48	0.05	0.55
Winter_WE_H17	0.48	0.35	0.49	-	0.55
Winter_WE_H18	0.48	0.34	0.49	-	0.55
Winter_WE_H19	0.48	0.34	0.49	-	0.55
Winter_WE_H20	0.48	0.34	0.49	-	0.55
Winter_WE_H21	0.48	0.34	0.48	-	0.55
Winter_WE_H22	0.48	0.33	0.48	-	0.55
Winter_WE_H23	0.48	0.32	0.48	-	0.55
Winter_WE_H24	0.48	0.31	0.48	-	0.55

Table 6.25: Summer Workdays Capacity Factors

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Summer_WD_H01	0.29	0.10	0.16	-	0.45
Summer_WD_H02	0.29	0.10	0.16	-	0.45
Summer_WD_H03	0.29	0.09	0.16	-	0.45
Summer_WD_H04	0.29	0.09	0.16	-	0.45
Summer_WD_H05	0.29	0.09	0.16	-	0.45
Summer_WD_H06	0.29	0.10	0.16	0.03	0.45
Summer_WD_H07	0.29	0.12	0.16	0.10	0.45
Summer_WD_H08	0.29	0.13	0.16	0.21	0.45
Summer_WD_H09	0.29	0.15	0.16	0.31	0.45
Summer_WD_H10	0.29	0.17	0.16	0.42	0.45
Summer_WD_H11	0.29	0.19	0.17	0.49	0.45
Summer_WD_H12	0.29	0.21	0.17	0.52	0.45
Summer_WD_H13	0.29	0.22	0.17	0.52	0.45
Summer_WD_H14	0.29	0.23	0.17	0.49	0.45
Summer_WD_H15	0.29	0.22	0.16	0.42	0.45
Summer_WD_H16	0.29	0.21	0.16	0.31	0.45
Summer_WD_H17	0.29	0.19	0.16	0.21	0.45
Summer_WD_H18	0.29	0.17	0.16	0.10	0.45
Summer_WD_H19	0.29	0.15	0.16	0.03	0.45
Summer_WD_H20	0.29	0.13	0.16	-	0.45
Summer_WD_H21	0.29	0.12	0.15	-	0.45
Summer_WD_H22	0.29	0.11	0.15	-	0.45
Summer_WD_H23	0.29	0.11	0.16	-	0.45
Summer_WD_H24	0.29	0.10	0.16	-	0.45

Table 6.26: Summer Weekends Capacity Factor

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Summer_WE_H01	0.29	0.10	0.16	-	0.45
Summer_WE_H02	0.29	0.10	0.16	-	0.45
Summer_WE_H03	0.29	0.09	0.16	-	0.45
Summer_WE_H04	0.29	0.09	0.16	-	0.45
Summer_WE_H05	0.29	0.09	0.16	-	0.45
Summer_WE_H06	0.29	0.10	0.16	0.03	0.45
Summer_WE_H07	0.29	0.12	0.16	0.10	0.45
Summer_WE_H08	0.29	0.13	0.16	0.21	0.45
Summer_WE_H09	0.29	0.15	0.16	0.31	0.45
Summer_WE_H10	0.29	0.17	0.16	0.42	0.45
Summer_WE_H11	0.29	0.19	0.17	0.49	0.45
Summer_WE_H12	0.29	0.21	0.17	0.52	0.45
Summer_WE_H13	0.29	0.22	0.17	0.52	0.45
Summer_WE_H14	0.29	0.23	0.17	0.49	0.45
Summer_WE_H15	0.29	0.22	0.16	0.42	0.45
Summer_WE_H16	0.29	0.21	0.16	0.31	0.45
Summer_WE_H17	0.29	0.19	0.16	0.21	0.45
Summer_WE_H18	0.29	0.17	0.16	0.10	0.45
Summer_WE_H19	0.29	0.15	0.16	0.03	0.45
Summer_WE_H20	0.29	0.13	0.16	-	0.45
Summer_WE_H21	0.29	0.12	0.15	-	0.45
Summer_WE_H22	0.29	0.11	0.15	-	0.45
Summer_WE_H23	0.29	0.11	0.16	-	0.45
Summer_WE_H24	0.29	0.10	0.16	-	0.45

Table 6.27: Mid-Season Workdays Capacity Factor

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
MidSeason_WD_H01	0.53	0.22	0.32	-	0.55
MidSeason_WD_H02	0.53	0.22	0.32	-	0.55
MidSeason_WD_H03	0.53	0.21	0.32	-	0.55
MidSeason_WD_H04	0.53	0.21	0.32	-	0.55
MidSeason_WD_H05	0.53	0.21	0.32	-	0.55
MidSeason_WD_H06	0.53	0.22	0.32	-	0.55
MidSeason_WD_H07	0.53	0.22	0.32	0.03	0.55
MidSeason_WD_H08	0.53	0.23	0.32	0.10	0.55
MidSeason_WD_H09	0.53	0.23	0.32	0.21	0.55
MidSeason_WD_H10	0.53	0.24	0.32	0.31	0.55
MidSeason_WD_H11	0.53	0.25	0.32	0.39	0.55
MidSeason_WD_H12	0.53	0.26	0.32	0.42	0.55
MidSeason_WD_H13	0.53	0.27	0.32	0.42	0.55
MidSeason_WD_H14	0.53	0.28	0.32	0.39	0.55
MidSeason_WD_H15	0.53	0.28	0.32	0.31	0.55
MidSeason_WD_H16	0.53	0.28	0.32	0.21	0.55
MidSeason_WD_H17	0.53	0.27	0.32	0.10	0.55
MidSeason_WD_H18	0.53	0.26	0.32	0.03	0.55
MidSeason_WD_H19	0.53	0.26	0.32	-	0.55
MidSeason_WD_H20	0.53	0.25	0.32	-	0.55
MidSeason_WD_H21	0.53	0.23	0.32	-	0.55
MidSeason_WD_H22	0.53	0.23	0.32	-	0.55
MidSeason_WD_H23	0.53	0.23	0.32	-	0.55
MidSeason_WD_H24	0.53	0.22	0.32	-	0.55

Table 6.28: Mid-Season Weekends Capacity Factors

Capacity factor	ROR	WIND ON	WIND OFF	PV	RESERVOIR
MidSeason_WE_H01	0.53	0.22	0.32	-	0.55
MidSeason_WE_H02	0.53	0.22	0.32	-	0.55
MidSeason_WE_H03	0.53	0.21	0.32	-	0.55
MidSeason_WE_H04	0.53	0.21	0.32	-	0.55
MidSeason_WE_H05	0.53	0.21	0.32	-	0.55
MidSeason_WE_H06	0.53	0.22	0.32	-	0.55
MidSeason_WE_H07	0.53	0.22	0.32	0.03	0.55
MidSeason_WE_H08	0.53	0.23	0.32	0.10	0.55
MidSeason_WE_H09	0.53	0.23	0.32	0.21	0.55
MidSeason_WE_H10	0.53	0.24	0.32	0.31	0.55
MidSeason_WE_H11	0.53	0.25	0.32	0.39	0.55
MidSeason_WE_H12	0.53	0.26	0.32	0.42	0.55
MidSeason_WE_H13	0.53	0.27	0.32	0.42	0.55
MidSeason_WE_H14	0.53	0.28	0.32	0.39	0.55
MidSeason_WE_H15	0.53	0.28	0.32	0.31	0.55
MidSeason_WE_H16	0.53	0.28	0.32	0.21	0.55
MidSeason_WE_H17	0.53	0.27	0.32	0.10	0.55
MidSeason_WE_H18	0.53	0.26	0.32	0.03	0.55
MidSeason_WE_H19	0.53	0.26	0.32	-	0.55
MidSeason_WE_H20	0.53	0.25	0.32	-	0.55
MidSeason_WE_H21	0.53	0.23	0.32	-	0.55
MidSeason_WE_H22	0.53	0.23	0.32	-	0.55
MidSeason_WE_H23	0.53	0.23	0.32	-	0.55
MidSeason_WE_H24	0.53	0.22	0.32	-	0.55

Table 6.29: Annual Capacity Factor

Technology	ROR	WIND ON	WIND OFF	PV	RESERVOIR
Capacity factor (Annual)	0.45	0.24	0.32	0.12	0.52

The CapacityFactor parameter represents the average available capacity of a technology as a fraction of its total design capacity for each specific time slice. While the Availability Factor covers internal maintenance, the Capacity Factor is used to model external constraints, such as weather and seasonal resource availability, that are beyond the operator's control.

In this model, the default value is set to 1 (no seasonal dependency) for dispatchable thermal plants. However, specific values and profiles have been defined for non-dispatchable renewables and hydroelectric reservoirs to reflect their natural variability.

To accurately model the temporal availability of renewable resources, the Capacity Factor for each specific time-slice (l) is calculated by distributing the annual average capacity factor (Table 6.29) according to the normalized resource profile of the technology. This methodology ensures that the sum of the energy produced across all time-slices remains consistent with the observed annual performance, while correctly fluctuating to simulate peak and off-peak generation periods.

In this study, the Capacity Factor is defined exclusively for non-dispatchable renewable technologies and hydroelectric reservoirs to accurately reflect their natural variability:

- Run-of-River (RoR): Annual average capacity factor of 0.45 is sourced from (IRENA, 2025) and distributed across time slices to reflect characteristic seasonal hydrological availability. Specifically, the model assumes peak water resources during the mid-season, intermediate availability in winter, and the lowest levels during the summer to account for characteristic dry periods.
- Solar PV: Annual average capacity factor of 0.12 is derived from (IRENA, 2025) (using 2023 data as already explained in model calibration phase). This value is distributed according to a profile that captures the typical daily bell-shaped curve and annual monthly variations as described by the source (Iain Staffell, Stefan Pfenninger, 2018).
- Wind Onshore and Offshore: Annual average capacity factors are derived from (IRENA, 2025) data (using 2023 data as already explained in model calibration phase) and distributed according to representative production profiles. Offshore wind is characterized by a significantly more stable and uniform generation profile, whereas onshore wind exhibits a more pronounced seasonal pattern. Specifically, the model assumes peak resource availability during the winter, followed by intermediate levels in the mid-season, and its lowest output during the summer, as reported in the source (Wind Europe, 2023). Furthermore, the diurnal distribution for onshore wind reflects a typical inland profile, with higher resource availability concentrated during the daytime and lower during night as described by the source (Yosef Ashkenazy, 2022). For Wind Offshore a more consistent trend over the day is assumed, as reported in (LUVSIDE, 2025).
- Hydro Reservoir: Annual average capacity factor of 0.52 is utilized to model resource dependence despite the basin's capacity. Its temporal distribution follows the same seasonal profile as Run-of-River, though the variation is modeled as less pronounced. The Capacity Factor is sourced from (IRENA, 2025).

The distribution of the Capacity Factor across time-slices depends solely on the distinction between seasons and the hour of the day. It does not differentiate between day-types (workdays and weekends), as the availability of natural resources remains unaffected by the human calendar. Table 6.23, Table 6.24, Table 6.25, Table 6.26, Table 6.27 and Table 6.28 report the assumed capacity factor profile for the different renewable energy technologies during Winter, Summer and Midseason workdays and weekends.

Total Annual Max Capacity

Table 6.30: Total Annual Max Capacity

Total Annual Max Capacity [GW]	2024	2025	2030	2035	2040	2045	2050
ROR	73.20	73.50	74.90	76.30	77.80	79.20	80.60

The TotalAnnualMaxCapacity parameter is used to impose an upper restriction on the overall installed capacity of a particular technology in a given year. Unlike the annual investment limit (which restricts how much new capacity can be added), this parameter defines the absolute upper limit that the total stock (existing plus new) cannot exceed.

In this modeling framework, this constraint is applied exclusively to Run-of-River (RoR) technology. The decision is based on the following technical and environmental considerations:

- According to estimates from (Joint Research Centre , 2024), the expansion potential for run-of-river hydropower in Europe is nearing its physical and environmental limit. Projections suggest that between now and 2050, the total capacity can only grow by approximately 8% compared to current levels.
- To accurately reflect this physical limitation, the total capacity cap is distributed across the model's time horizon, as reported in Table 6.30. Instead of allowing for sudden growth, a maximum annual capacity linear trajectory is defined to gradually guide the system toward the 8% limit projected for 2050.

Total Technology Annual Activity Upper Limit

Table 6.31: Total Technology Annual Activity Upper Limit

Total Technology Annual Activity Upper Limit [TWh]	2024	2025	2030	2035	2040	2045	2050
RESERVOIR	374.0	374.0	374.0	374.0	374.0	374.0	374.0
BIO	191.9	192.7	196.3	200.0	203.7	207.3	211.0

The TotalTechnologyAnnualActivityUpperLimit parameter is utilized to establish an upper limit on the total annual generation (activity) of a specific technology. This constraint ensures that the model respects physical, environmental, or resource-based limitations.

In this study, this limit is applied specifically to two key energy sources, as reported in Table 6.31:

- For Hydro Reservoir technologies, the annual activity limit is set to remain constant throughout the entire modeling horizon, according to the source (Joint Research Centre , 2024). The maximum production for every year until 2050 is fixed at the observed 2024 generation levels. This assumption reflects the mature nature of the European hydroelectric fleet and the lack of remaining undeveloped sites for large-scale reservoirs, effectively capping production at current historical levels.
- For Biomass, the activity limit is used to model the fundamental scarcity of sustainable bio-resource. The 2050 production upper limit is derived through a bottom-up calculation based on projections from (Concawe, 2022): The projected total bioenergy available in 2050 is estimated at 366 Mtoe. Following historical and projected trends, it is assumed that 15% (Joint Research Centre , 2019) of this total energy resource is dedicated to electricity production, resulting in 55 Mtoe for the power sector. Applying a conversion efficiency of 0.33, this primary energy translates to approximately 211 TWh of electricity. To ensure a realistic transition, the model does not jump immediately to these limits. Instead, a linear trajectory is defined for Biomass, connecting the 2024 production level to the estimated 211 TWh limit in 2050. This gradual increase reflects the progressive maximum scaling of the biomass supply chain for electricity production.

6.2. Stated Policy Scenario Modelling Inputs

Capital Cost

Table 6.32: STEPS Scenario Capital Cost

Capital Cost ($/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	6,600	6,350	5,100	4,950	4,800	4,650	4,500
WIND ON	1,630	1,617	1,550	1,535	1,520	1,505	1,490
WIND OFF	3,120	2,980	2,280	2,125	1,970	1,815	1,660
PV	750	705	480	445	410	375	340
BIO	4,370	4,340	4,192	4,044	3,896	3,748	3,600
GEO	5,000	5,000	5,000	5,000	5,000	5,000	5,000
RESERVOIR	3,600	3,600	3,600	3,600	3,600	3,600	3,600
ROR	3,500	3,500	3,500	3,500	3,500	3,500	3,500
CCGT	1,000	1,000	1,000	1,000	1,000	1,000	1,000
COAL	2,000	2,000	2,000	2,000	2,000	2,000	2,000
SCGT	700	700	700	700	700	700	700
PHES	2,000	2,000	2,000	2,000	2,000	2,000	2,000
BATT	300	299	293	287	282	276	270
OIL	600	600	600	600	600	600	600
COAL CCS	5,500	5,482	5,391	5,300	5,117	4,933	4,750
GAS CCS	3,100	3,086	3,010	2,950	2,850	2,750	2,650

The CapitalCost parameter specifies the investment costs associated with the construction or installation of a technology. It represents the initial capital expenditure (CAPEX) required to acquire, construct, or expand new capacity, expressed as the cost per unit of capacity (e.g., M$/GW).

The evolution of capital costs in the model, as reported in Table 6.32, reflects technological learning and market maturity, with projections sourced from leading international energy institutions:

- IEA Steps Scenario Technologies: For CCS-equipped plants, Gas and Coal, the capital costs are aligned with the European projections provided in (IEA, 2025) for the reference years 2030 and 2050 for the Steps Scenario. For Nuclear, Coal, CCGT, Solar PV, and Wind (Onshore and Offshore), the capital costs are aligned with the Steps Scenario European projections provided in (IEA, 2024), for the reference years 2030 and 2050.
- Biomass: The cost reduction trend for this technology is consistent across all three simulated scenarios and follow the trajectories established by the (NREL, 2024) up to 2050, starting from the assumed 2024 value.
- Battery Storage (Power Component): For the power conversion component of battery systems, the model adopts the cost reduction trajectory of the Conservative Scenario sourced in (NREL, 2024), reflecting a cautious but

steady decline in hardware costs up to 2050. The decision to utilize NREL 2024 data for this specific parameter, rather than the projections provided by the IEA, is driven by a technical modelling requirement. Unlike other sources, the NREL database provides a clear distinction between the power component (inverters, power electronics) and the storage component (energy capacity). This disaggregation is essential for the modelling framework used in this study, which requires these two elements to be treated separately to independently optimize both discharge/charge capacity and energy storage volume.

- Constant Cost Baseline: For all other technologies not explicitly cited, capital costs are assumed to remain constant through to 2050. This conservative approach is adopted due to the absence of specific, reliable forecasts regarding CAPEX reductions for these assets.

To ensure a continuous and realistic transition between the specific data points, specifically for the technologies whose projections are sourced from the (IEA, 2025) and (IEA, 2024), the model applies a linear reduction for the intermediate years.

For these technologies:

- A linear slope is calculated between the base year (2024) and 2030.
- A second linear slope is applied for the period between 2030 and 2050.

This approach allows the model to capture the anticipated "learning by doing" and economies of scale for the primary generation fleet, making these technologies increasingly competitive over the 2024–2050 horizon.

Under the Copperplate assumption, the model does not account for the investment or operational costs of Transmission and Distribution (T&D) infrastructure. This approach allows the system to freely define the required capacity in GW necessary to balance the grid, assuming no internal bottlenecks or financial constraints on the expansion of the network itself.

The 2024 Capital Cost for Coal CCS and Gas CCS is sourced from (IEA, 2025), for Coal, CCGT, Nuclear, Wind On, Wind Off and PV is sourced from (IEA, 2024), for Run-of-River, Reservoir, Pumped Hydro the mean value from (IEA, NEA, OECD, 2020) is assumed. For Geothermal the capital cost is sourced from (LAZARD, 2025), for biomass the average between (Fraunhofer ISE, 2024) and (IRENA, 2025) is assumed. For SCGT the capital cost is sourced from (Fraunhofer ISE, 2024), for battery the capital cost of the power component is sourced from (NREL, 2024).

Fixed Cost O&M

Table 6.33: STEPS Scenario Fixed O&M Cost [% of Capex]

Technology	Fixed O&M Cost [% of Capex Cost]
SCGT	2.75%
COAL	2%
OIL	2.75%
BIO	3.75%
GEO	3.50%
RESERVOIR / ROR	2%
CCGT	2%
PV	1.35%
WIND ON	2%
NUC	2%
WIND OFF	2%
PHES	2%
BATT	2%
COAL CCS	3%
GAS CCS	2%

Table 6.34: STEPS Scenario Fixed O&M Cost

Fixed O&M Cost ($/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	132.0	127.0	102.0	99.0	96.0	93.0	90.0
WIND ON	32.6	32.3	31.0	30.7	30.4	30.1	29.8
WIND OFF	78.0	74.5	57.0	53.1	49.3	45.4	41.5
PV	10.1	9.5	6.5	6.0	5.5	5.1	4.6
BIO	163.9	162.8	157.2	151.7	146.1	140.6	135.0
GEO	175.0	175.0	175.0	175.0	175.0	175.0	175.0
RESERVOIR	72.0	72.0	72.0	72.0	72.0	72.0	72.0
ROR	70.0	70.0	70.0	70.0	70.0	70.0	70.0
CCGT	20.0	20.0	20.0	20.0	20.0	20.0	20.0
COAL	40.0	40.0	40.0	40.0	40.0	40.0	40.0
SCGT	19.3	19.3	19.3	19.3	19.3	19.3	19.3
PHES	40.0	40.0	40.0	40.0	40.0	40.0	40.0
OIL	16.5	16.5	16.5	16.5	16.5	16.5	16.5
BATT	20.0	19.0	14.0	13.1	12.2	11.3	10.4
COAL CCS	165.0	164.5	161.7	159.0	153.5	148.0	142.5
GAS CCS	77.5	77.2	75.3	73.8	71.3	68.8	66.3

The FixedCost parameter specifies the expenditure required to maintain a technology's availability and operational readiness, regardless of its actual generation level. These costs are defined on a per-unit-of-capacity basis (e.g., M$/GW) and can evolve annually to reflect the changing economic landscape of the power fleet.

In this modeling framework, fixed operation and maintenance (O&M) costs are directly linked to the investment of technology.

- Percentage-Based Calculation: Fixed O&M costs are calculated as a fixed percentage of the Capital Cost (CAPEX). Table 6.33 reports the assumed % for the different technologies.
- Consistency Across Scenarios: This percentage remains constant across all modeled years and all simulated scenarios.
- Dynamic Cost Evolution: Although the percentage is fixed, the absolute monetary value of the fixed cost varies over time, as reported in Table 6.34. Because it is tied to the CAPEX, which decreases over the simulation period due to technological learning curves, the fixed O&M costs decrease accordingly. This reflects the reality that as technologies become cheaper and more standardized, their baseline maintenance requirements often become more cost-efficient as well.

A specific approach is adopted for battery systems to ensure all maintenance aspects are captured within a single economic parameter. While the CAPEX for batteries is split between power and storage components (using (NREL, 2024)), the fixed O&M cost is calculated based on the total CAPEX provided by (IEA, 2024).

Since the IEA WEO 2024 report provides an aggregated investment figure that does not distinguish between the power conversion system and the energy reservoir, it serves as a comprehensive baseline for maintenance. Using this "all-in" CAPEX allows the model to derive a single fixed cost that covers the maintenance of the entire battery installation, ensuring the economic representation remains consistent with global market projections.

Regarding the fixed cost of Operation and Maintenance (FOM), expressed as a percentage of the CAPEX, various sources are consulted. Since many references provide FOM costs in absolute terms (e.g., $/kW), the percentage values are derived by dividing the annual O&M cost by the corresponding CAPEX reported within the same source.

The fixed O&M cost (%) for Gas CCS and Coal CCS is sourced from (IEA, 2025), for Nuclear is sourced from (Timilsina, 2020). For Geothermal the mean value between (Timilsina, 2020) and (IRENA, 2024) is assumed, for SCGT the mean value between (Fraunhofer ISE, 2024) and (LAZARD, 2025) is assumed, for Run-Of-River, Reservoir and Pumped Hydro the mean value between (Timilsina, 2020) and (IRENA, 2025) is assumed. For Coal, CCGT, Wind On the mean value of (Fraunhofer ISE, 2024) is assumed. For Oil the same % as SCGT is assumed. For PV, Wind Off and Biomass the average between (Timilsina, 2020) and the mean value of

(Fraunhofer ISE, 2024) is assumed. The fixed cost for Battery is sourced from (NREL, 2024).

Fuel Cost

Table 6.35: STEPS Scenario Fuel Cost

Fuel Cost ($/MWh)	2024	2025	2030	2035	2040	2045	2050
COAL	16.0	15.6	13.4	11.1	10.6	10.0	9.4
OIL	46.5	46.5	46.8	47.1	46.3	45.5	44.7
GAS	35.1	34.0	28.1	22.2	24.3	26.5	28.7
URANIUM	9.0	9.0	9.0	9.0	9.0	9.0	9.0
BIO	39.6	39.6	39.6	39.6	39.6	39.6	39.6

The Fuel Cost parameter defines the expenditure required to procure the energy carriers necessary for plant operation. Table 6.35 reports the fuel costs assumed for the STEPS Scenario.

For the primary fossil commodities, Natural Gas, Coal, and Oil, the model adopts the price trajectories specifically projected for the European market in the Steps Scenario sourced in (IEA, 2025).

- Linear Interpolation: To ensure a realistic and continuous transition between global energy milestones, the price evolution is modeled using a linear interpolation between the base year (2024) and 2035 milestone, and subsequently between 2035 and 2050. This approach reflects the anticipated long-term shifts in supply-demand balances and regional market trends.

To ensure methodological consistency within the modeling framework, oil, coal and natural gas prices, sourced in (IEA, 2025), are converted from their respective commercial trading units into a uniform energy-based metric (USD/MWh).

The conversion process relies on the following international technical standards and physical constants:

- Hard Coal: Prices quoted in mass units (USD/t) are divided by a factor of 7. This value represents the average energy content of a Tonne of Coal Equivalent (tce), which corresponds to a Lower Heating Value (LHV) of approximately 7 MWh per metric tonne of high-quality coal (Nunes, Matias, Loureiro, & Al., 2021).
- Oil: The price per barrel (USD/bbl) is divided by 1.7. This coefficient reflects the average energy density of crude oil, which is approximately 1.7 MWh per barrel (IPAA, s.d.). This allows for the normalization of the cost based on the thermal energy content of the liquid fuel.
- Natural Gas: Prices expressed in USD/MMBtu are multiplied by 3.412. This factor is derived from the standard thermal conversion constant, where 1

MWh is exactly equivalent to 3.412 MMBtu. This multiplication translates the cost from the Anglo-Saxon thermal unit to the energy standard required by the model.

By applying these conversions, the model ensures that all fuel inputs their actual primary energy content.

In the absence of specific long-term price projections from the IEA for nuclear fuel, the cost of Uranium is assumed to remain constant throughout the simulation period (2024–2050) and the fuel cost is sourced in (Fraunhofer ISE, 2024). This assumption is because fuel costs represent a relatively small and historically stable portion of the total levelized cost of nuclear electricity compared to capital and decommissioning expenses.

A dedicated bottom-up approach is used to estimate a representative fuel cost for the Biomass category. This value is maintained as a constant throughout the modeling horizon and is derived from a weighted average calculation based on the 2023 European bioenergy mix reported in (European Commission, 2023):

- Feedstock Composition: The 2023 mix is composed of 52.5% Solid Biomass, 34.0% Biogas, and 12.5% Renewable Municipal Waste (RMW).
- Cost Assumptions:
  - Renewable Municipal Waste (RMW): Assigned a zero-fuel cost, as it is considered a byproduct of waste management services.
  - Solid Biomass and Biogas: Specific unit fuel costs are sourced from (Fraunhofer ISE, 2024).
- Calculation: The final biomass fuel price is the weighted average of these components, providing a realistic economic baseline that accounts for the different types of bio-resources utilized across Europe.

Comparative Analysis of Natural Gas Price Trajectories

A comparison between EU historical market data and (IEA, 2025) projections for natural gas highlights a distinct shift from the extreme volatility of the early 2020s toward a period of projected structural stabilization, as in Figure 6.1. Historical data show an unprecedented price peak in 2022, reaching levels above 300 EUR/MWh; this spike is primarily attributed to the global energy crisis and supply disruptions triggered by the Russia-Ukraine conflict.

In contrast, the IEA outlook assumes a starting price of 35.1 $/MWh in 2024, followed by a downward trend (in the STEPS) to a minimum of 22.2 $/MWh by 2035, and a subsequent recovery toward 28.7 $/MWh by 2050. It is essential to note that these price trajectories do not attempt to represent the fluctuations and price cycles that characterize commodity markets in practice. Instead, they provide a smooth, long-term equilibrium view. While the historical trend is defined by geopolitical shocks and cyclical volatility, the IEA projections focus on the underlying evolution of supply and demand dynamics within the global gas market over the coming decades.

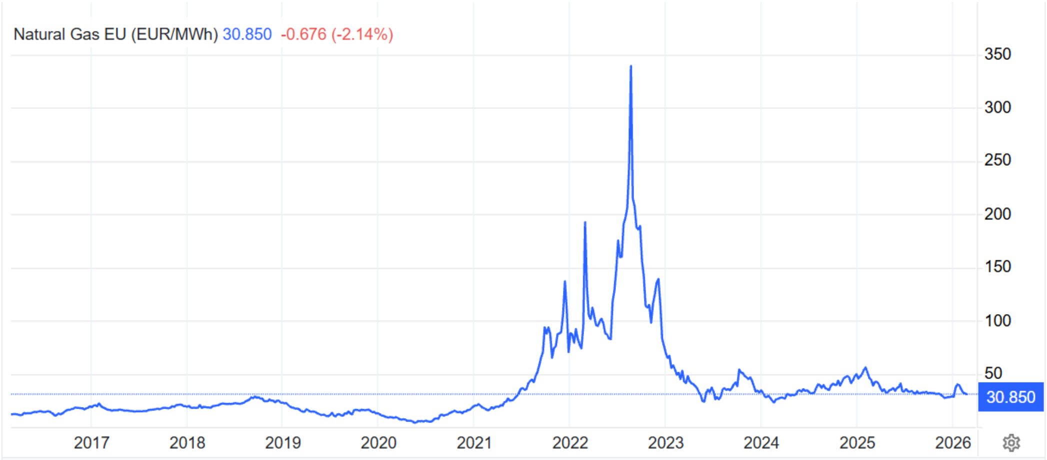

Figure 6.1: Historical Natural Gas Fuel Cost Variations (Trading Economics, 2026)

Comparative Analysis of Coal Price Trajectories

Following a similar pattern, the coal price evolution (in the STEPS) reflects a transition from high historical volatility toward a long-term downward trend in the IEA scenarios, as in Figure 6.2. The historical time series shows an unprecedented peak in 2022, where prices surged beyond 400 USD/t as a direct consequence of the global energy crisis and the supply shocks triggered by the Russia-Ukraine conflict.

Consistent with its overall methodology, the IEA assumes a starting price of 112 USD/t in 2024, which is projected to decline to 66 USD/t by 2050. These international prices are derived through iterative modeling and reflect the levels required to stimulate sufficient investment in supply to meet projected demand. As with the natural gas pathways, these trajectories do not attempt to represent the fluctuations and price cycles that characterize commodity markets in practice. Instead, they serve as fundamental drivers for fossil fuel supply and demand projections, providing a smooth, investment-oriented outlook that assumes the gradual stabilization of global markets.

Figure 6.2: Historical Coal Fuel Cost Variations (Trading Economics, 2026)

Emission Penalty

Table 6.36: STEPS Scenario Emission Penalty

Year	2024	2025	2030	2035	2040	2045	2050
Emission Penalty [$/Ton]	75	82	117	145	149	154	158

The Emissions Penalty parameter is used to assign a monetary cost to the release of pollutants into the atmosphere. In the context of this model, it represents a formal Carbon Tax or carbon price (e.g., within the EU Emissions Trading System framework), expressed in currency units per unit of emission (e.g., M$/Mton CO_2).

The price trajectory for carbon emissions reported in Table 6.36 is aligned with the European Steps Scenario projections sourced in (IEA, 2024). To ensure a smooth transition between long-term policy targets, the model applies a linear interpolation across two distinct periods, using 2035 and 2050 values sourced in (IEA, 2024):

- 2024–2035: Reflecting the initial ramp-up and strengthening of climate policies.
- 2035–2050: Reflecting the long-term stabilization or continued increase required to meet net-zero objectives.

The starting value for 2024 has been established as an average within the range of carbon taxes applied across the European Union during that year. This baseline accounts for the fluctuation in the EU ETS prices, which averaged around €65-80/tCO_2 in 2024 (Tradings Economics, s.d.).

Capital Cost Of Storage

Table 6.37: STEPS Scenario Capital Cost of Storage

Capital Cost of Storage ($/KWh)	2024	2025	2030	2035	2040	2045	2050
BATT	288	287	285	282	280	277	275

The CapitalCostStorage parameter specifies the investment costs associated with the energy capacity of a storage facility. It represents the capital expenditure (CAPEX) required to acquire or expand the actual energy reservoir expressed as the cost per unit of energy capacity (e.g., M$/PJ).

A distinct approach has been applied to the two primary storage technologies to reflect their specific technical and economic structures:

- Battery Storage (Energy Component): The linear cost projections for the energy-specific part of the battery systems follow the NREL 2024 Conservative Scenario up to 2050, sourced from (NREL, 2024). Similar to the power component, this choice is made because the NREL 2024 database provides a clear disaggregation between the costs that scale with power (inverters and electronics) and those that scale with duration (the battery modules themselves). By using the conservative trajectory, the model assumes a cautious but steady decline in the cost of lithium-ion (or equivalent) cells through 2050.
- Pumped Hydro Storage (PHS): For Pumped Hydro, the model assumes that the investment costs are entirely concentrated on the power component (turbines, pumps, and the powerhouse). Consequently, the CapitalCostStorage for PHS is set to zero and is not reported in Table 6.37. This modeling choice is primarily driven by the fact that standard economic sources and literature for Pumped Hydro typically do not distinguish between power ($/kW) and energy storage ($/kWh) costs, providing instead a single aggregated figure. By focusing the total cost on the power side, the model aligns with available data formats while accurately reflecting that the primary economic burden lies in the electromechanical equipment and large-scale civil engineering works.

Specified Annual Demand

Table 6.38: STEPS Scenario Specified Annual Demand

Specified Annual Demand [TWh]	2024	2025	2030	2035	2040	2045	2050
ELC_SERVICE	1,116	1,137	1,240	1,344	1,447	1,550	1,654
ELC_RES	1,011	1,013	1,023	1,033	1,043	1,053	1,063
ELC_IND	1,255	1,277	1,388	1,499	1,610	1,720	1,831
ELC_MOB	105	153	394	635	876	1,117	1,359
Aggregated Electricity	3,487	3,580	4,045	4,511	4,976	5,442	5,907

The SpecifiedAnnualDemand parameter is a fundamental parameter of the OSeMOSYS framework, since the model is ‘demand-driven’.

For this study, the total annual electricity demand for the years 2024 and 2050 for the Stated Policies Scenario (STEPS) is sourced from the World Energy Outlook (WEO) 2025 (IEA, 2025) European Steps projections.

To provide a granular representation of the European power system, the following methodological steps are implemented:

- Baseline Sectoral Split (2024): The total European electricity demand for 2024 is disaggregated into four key sectors: Industry, Residential, Commercial/Services, and Transport, respectively defining the ELC_IND, ELC_RES, ELC_SERVICE and ELC_MOB demand for 2024, as reported in Table 6.38. The Residential sector in 2024 accounts for 29% of total demand, the service sector for 32%, the industry sector for 36% and mobility for 3%, as reported in (IEA, 2023).
- Future Sectoral Split (2050): The projected total demand for 2050 is similarly broken down into these four sectors, accounting for long-term trends such as increased electrification in transport and heating. The Residential sector in 2050 accounts for 18% of total demand, the service sector for 28%, the industry sector for 31% and mobility for 23%. 2050 percentages are an extrapolation to 2050 of the evolution projected by (TERNA, 2025).
- Linear Growth Trajectory: Between the base year (2024) and the final year (2050), the demand for each individual sector is assumed to follow a linear growth profile. This ensures a continuous and stable evolution of demand throughout the simulation period.

A key assumption of this model is that the percentage distribution of total demand among the four sectors remains constant across all three analyzed scenarios for both the 2024 and 2050 data points.

Total Annual Max Capacity Investment

Table 6.39: STEPS Scenario Total Annual Max Capacity Investment

Total Max Capacity Inv. [GW]	2024	2025	2026	2027	2028	2029	2030	2031	2035	2040	2045	2050
PHES	-	3	3	3	3	3	3	2	2	2	2	2
BATT	1	15	30	35	50	50	50	50	50	70	70	70
COAL CCS	-	1	1	1	1	1	1	1	1	1	1	1
GAS CCS	-	2	2	2	2	2	2	3	5	5	5	5
WIND ON	-	20	20	25	25	25	25	30	30	30	30	30
WIND OFF	-	10	15	20	20	30	30	30	40	40	40	40
PV	-	70	70	70	70	70	70	80	90	100	100	100
BIO	-	5	5	5	5	5	5	5	5	5	5	5
RESERVOIR	-	-	-	-	-	-	-	-	-	-	-	-
GEO	-	-	-	-	-	-	-	-	-	-	-	-
NUC	-	3	3	3	4	4	5	5	5	8	8	8
SCGT	-	4	4	4	4	4	4	4	4	4	3	3
COAL	-	-	-	-	-	-	-	-	-	-	-	-
OIL	-	-	-	-	-	-	-	-	-	-	-	-
CCGT	-	10	10	10	10	10	10	8	6	6	5	5

The TotalAnnualMaxCapacityInvestment parameter is used to impose physical, logistical, or industrial constraints on the speed at which a specific technology can be deployed within the system. It establishes a direct upper bound on the amount of new capacity that can be installed in any single year, preventing the model from selecting unrealistic "overnight" transformations that the actual market or supply chain could not support.

To ensure the energy transition is both ambitious and grounded in industrial reality, specific deployment trajectories are established for storage power technologies via the TotalAnnualMaxCapacityInvestment parameter, as reported in Table 6.39. These limits reflect the distinct market maturity and physical constraints of electrochemical and mechanical storage.

The investment limit for battery storage follows a growth strategy designed to support increasing levels of renewable integration and sector electrification:

- For the early years of the simulation, the model allows for a strong and rapid expansion, driven by the observed 2024 Compound Annual Growth Rate (CAGR) of 45.6% for Europe (Energy Institute, 2025).
- Around 2030, the annual investment limit reaches an assumed stable plateau of +50 GW per year, representing a mature industrial supply chain capable of consistent large-scale delivery.
- From 2037 onwards, the annual limit is deliberately increased. This ‘push’ provides the system with the necessary flexibility to manage the final stages of the transition, specifically addressing the rise in electricity demand and the total decommissioning of the fossil-fuel fleet. this accelerated limit was set to favour the significant cost reductions assumed for the latter half of the projection.

The development profile for Pumped Hydro follows an inverse logic to that of batteries, focusing on early-system stabilization while respecting physical land-use limits:

- The highest annual investment limits are concentrated in the first years of the simulation. This deployment is intended to provide the European grid with immediate, large-scale long-duration storage and inertia to favour the initial phase of the transition.
- Over time, the annual deployment rate is modelled to slow down significantly. This reflects the increasing scarcity of suitable topographical sites for new dams and reservoirs.
- Unlike batteries, the total cumulative capacity for Pumped Hydro is limited by a physical and geographical limit. The maximum installable power for 2050 is sourced from (Emanuele Quaranta, 2024). To ensure realistic modelling, the annual investment limits are defined by distributing this total maximum potential across the entire period from 2024 to 2050, ensuring the

model remains within the technical and environmental potential of the European landscape.

For Solar PV, Onshore Wind, and Offshore Wind, the investment limits defined by the TotalAnnualMaxCapacityInvestment parameter follow an increasing deployment curve, as reported in Table 6.39. This trajectory is designed to reflect both recent historical growth and the ambitious policy targets outlined in current energy transition roadmaps.

The starting point for the annual investment limits is based on the observed performance of the European renewable energy market over the last five years:

- Solar PV: The initial limit is set in line with the record-breaking installations seen in 2023, where approximately +68 GW of new capacity were added across Europe (EMBER, 2024).
- Wind (Onshore and Offshore): The initial limit follows the historical growth trend exemplified by the +20 GW added in 2021, providing a realistic baseline for the wind sector's current industrial capacity (EMBER, 2024).

Beyond the base year, the deployment limits are modelled to increase progressively, following the policy framework of the WEO 2024 European Stated Policies Scenario (STEPS) (IEA, 2024). This scenario assumes that existing and stated policies will provide a continuous push for renewable expansion to meet decarbonization targets.

The model reflects this by allowing the annual installation capacity to grow each year, assuming that as the industry scales, supply chains, permitting processes, and the specialized workforce will expand to support higher deployment volumes.

From 2035 onwards, the model assumes a higher maximum annual installation capacity for Offshore Wind compared to Onshore Wind. This strategic assumption is driven by the more pronounced capital cost reductions projected for offshore technology relative to onshore in the WEO 2024 Step Scenario capex projections, as well as the strong policy assumptions and strategic priority assigned to offshore deployment within the STEPS scenario (IEA, 2024).

To align the model with the environmental and physical realities of the European energy landscape, additional restrictive bounds have been applied to specific technologies within the TotalAnnualMaxCapacityInvestment framework, as reported in Table 6.39. These constraints reflect policy-driven phase-outs, low availability of suitable geographical sites, and resource availability limitations.

In accordance with the WEO 2024 Stated Policies Scenario (STEPS), which assumes in its policy (IEA, 2024) a definitive transition away from the most carbon-intensive fuels in Europe, the model is set to not invest in any new Coal or Oil-fired capacity throughout the entire 2024–2050 horizon. This constraint reflects the active coal phase-out policies adopted by most European member states and the lack of economic or political incentives for new oil-based power generation in a decarbonizing grid.

For certain mature or geographically dependent technologies, further expansion is considered technically or environmentally unfeasible:

- Conventional Geothermal: No new installations are assumed for traditional hydrothermal plants. As noted in (Joint Research Centre, 2024), while geothermal heat has potential, the sites suitable for conventional high-temperature electricity generation in Europe are largely already exploited or face high geological risk, shifting the focus toward next-generation Enhanced Geothermal Systems (EGS). Additionally, since geothermal capacity in Europe and Turkey has plateaued since 2019 (Our World in Data, 2025), the model assumes no further expansion of conventional geothermal power. This trend-based assumption aligns with historical data indicating limited development of new traditional geothermal fields in the region.
- Hydro Reservoirs: Like conventional geothermal, a "no new installation" rule is applied to large-scale hydroelectric reservoirs, as noted in (Joint Research Centre , 2024).

The investment profile for nuclear energy follows a progressive growth curve, characterized by a slow start followed by an accelerating deployment:

- The initial low values represent the significant "lead time" required for the planning, permitting, and multi-year construction of nuclear assets.
- This trajectory aligns with the renewed push for nuclear power within the IEA WEO 2024 STEPS scenario. According to (Global Energy Monitor, 2025), Europe currently has over 10 GW of capacity under construction, with several more gigawatts in pre-construction phases.
- As we move toward 2050, the investment limit increases, supported by the anticipated reduction in capital costs projected by the WEO 2024 (IEA, 2024).

For gas technologies, specifically Combined Cycle Gas Turbines (CCGT) and Simple Cycle Gas Turbines (SCGT), the model assumes a development profile characterized by a slight decrease following an initial strategic peak. This early expansion in gas capacity is permitted to facilitate the accelerated decommissioning of coal and oil plants, accommodate rising electricity demand, and replace the aging European fleet identified in the Residual Capacity analysis.

To reflect their distinct operational roles, two different maximum development profiles are implemented:

- CCGT: This technology is assigned a higher initial investment limit, reflecting its significantly larger current installed base and historical dominance compared to SCGT. However, the maximum capacity investment for CCGT follows a more pronounced reduction over the planning horizon. This is due to its traditional function as a baseload/mid-load plant, a role that becomes less competitive as carbon prices rise and cheaper renewable alternatives expand.
- SCGT: While starting with a lower limit, SCGT profiles are designed to support system flexibility. Toward the end of the planning horizon, the high penetration of variable renewable energy (VRE) necessitates a shift from mid-load generation toward flexible peaking technologies. Consequently, it is assumed a greater long-term strategic need for SCGT to provide grid stability and peak-shaving, rather than CCGT for mid-load supply.

Based on historical data, such as the 2007 peak in Spain where 5.6 GW of CCGT were installed in a single year (Enagas, 2008), the total European industrial gas capacity is capped at an assumed maximum of 15–20 GW/year.

For Biomass, a maximum annual investment limit of 5 GW is established. This choice assumes that the main constraint on bioenergy expansion is not merely technical capacity, but the availability of the sustainable resource itself; consequently, the primary cap on biomass contribution is modelled through the Upper Activity Limit (which restricts total annual production).

The deployment of Gas+CCS and Coal+CCS is strictly tied to the development of CO_2 transport and storage infrastructure.

The realistic deployment is limited by the capacity of storage hubs. For example, projects like NZT Power (NZT Power, 2026) (≈0.74 GW) and Keadby 3 (SSE Thermal, 2026) (≈0.91 GW) capture between 1.5 and 2 $MtCO_2$/Year. Essentially, 1 GW of Gas+CCS requires roughly 1.5-2 $MtCO_2$/Year of storage capacity. Current hubs such as Porthos (Porthos, 2026) (≈2.5 Mt/Year) or the initial phase of Northern Lights (Northen Ligths, 2026) (≈1.5 Mt/Year) can only support the emissions of 1-2 GW of power capacity each.

While the EU targets ≥ 50 Mt CO_2/Year (European Commission, 2024) of injection capacity by 2030, this must be shared with hard-to-abate sectors (cement, steel, chemicals) which often have priority. Consequently, the investment limit is set at a modest 1-3 GW/Year until 2030. Only after 2035, as North Sea clusters and continental hubs scale up (> 5 Mt/Year per hub) (North Sea Energy , 2026), the limit increase to 3-5 GW/Year favouring Gas+CCS due to its lower specific emissions compared to Coal+CCS.

Furthermore, under the Copper Plate assumption, no deployment limits are applied to Transmission and Distribution (T&D) infrastructure.

Finally, for the year 2024, the maximum capacity investment for all technologies is set to zero, with the only exception of battery storage, to account for uncertainties regarding the residual capacity of the existing storage fleet.

Technology Annual Activity Increase Limit

Table 6.40: STEPS Scenario Annual Activity Increase Limit

Max Increase [%] of Production	2024	2025	2030	2035	2040	2045	2050
WIND ON	25%	30%	30%	30%	20%	10%	10%
WIND OFF	25%	30%	35%	35%	30%	20%	20%
PV	25%	30%	30%	30%	20%	10%	10%
ROR	0%	0%	0%	0%	0%	0%	0%
BIOMASS	5%	5%	10%	10%	10%	10%	10%
NUCLEAR	5%	5%	10%	10%	10%	10%	10%
CCGT	15%	15%	15%	10%	10%	10%	5%
SCGT	15%	15%	15%	10%	10%	10%	5%

The TechnologyActivityIncreaseByModeLimit is used to manage the rate of the energy transition, avoiding unrealistic year-over-year spikes in generation. It defines the maximum allowable percentage increase in a technology's activity from one year to the next (e.g., a value of 0.1 allows a 10% increase).

For Solar PV, Onshore Wind, and Offshore Wind, the limits reported in Table 6.40 are initially calibrated against the highest growth rates observed in Europe over the last five years:

- In 2022, European Solar PV generation grew by +25% (EMBER, 2025), while Wind grew by +12% (EMBER, 2025). A slightly wider (more generous) growth limit is chosen initially for wind to account for the need to replace an aging fleet. These rates are modelled to increase over the mid-term of the simulation to facilitate the transition driven by falling technology costs. Toward the end of the 2050 horizon, the growth rates are gradually reduced, as new generation only needs to follow the incremental demand growth rather than a total system transition.
- For Offshore Wind a slightly higher maximum growth percentage is assumed to reflect the rapid cost-competitiveness projected for this sector.

For thermal and bioenergy technologies, the limits reported in Table 6.40 are set to allow for higher model flexibility while remaining within realistic industrial bounds:

- Gas-fired Power: The annual activity increase limit is initially set at +15%. This higher upper limit, significantly above the historical 5-year European peak of approximately +7% (EMBER, 2025), is intentionally designed to provide the model with the flexibility to rapidly scale up gas generation if necessary, to facilitate the decommissioning of coal and oil assets. Following this initial transition phase, the growth limit is gradually reduced over the subsequent years to align with the long-term goal of stabilizing the fleet and ensuring its eventual decarbonization.

- Biomass: Deployment limits is set to +10%. This follows the historical European peak of roughly +7% (EMBER, 2025).
- Nuclear Power: A more gradual growth profile is applied. This reflects the long lead times required for power upgrades, life extensions, or the commissioning of new reactors, ensuring that nuclear activity does not fluctuate unrealistically.
- Run-of-River (RoR) Hydro: This technology is assigned a null annual growth limit. While the model is permitted a slight capacity increase (up to 8% by 2050), this activity limit ensures that actual generation remains nearly constant, accurately reflecting the physical limits of European river basins and water availability.

Table 6.40 presents the Annual Max Activity Increase values for the specific technologies for which a constraint is modeled. Technologies not listed in Table 6.40 are not subject to this specific constraint, as other existing constraints already indirectly regulate their activity.

Technology Annual Activity Decrease Limit

Table 6.41: STEPS Scenario Annual Activity Decrease Limit

Max Decrease [%] of Production	2024	2025	2030	2035	2040	2045	2050
BIO	5%	5%	5%	5%	5%	5%	5%
NUC	5%	10%	10%	10%	10%	10%	10%
CCGT	15%	18%	35%	51%	67%	84%	100%
COAL	25%	29%	46%	64%	82%	100%	100%
OIL	25%	29%	46%	64%	82%	100%	100%
SCGT	15%	18%	35%	51%	67%	84%	100%

The TechnologyActivityDecreaseByModeLimit parameter is used to ensure that the generation (activity) of a specific technology does not decline more than a certain percentage each year. This is essential for preventing unrealistically activity reductions that could compromise system stability or ignore secondary uses of certain technologies (such as heat production).

The decrease limits reported in Table 6.41 are calibrated by comparing historical maximum reduction rates observed in Europe over the last five years against the strategic goals of the energy transition:

- Biomass: A fixed 5% annual decrease limit is applied throughout the entire period. This ensures that biomass production remains relatively stable, underling its dual role in providing both electricity and district heating or industrial process heat.

- Natural Gas: The maximum allowable decrease starts at 15% and increases linearly to 100% by 2050. While the historical maximum decrease from year 2000 for gas in Europe was around 8% (EMBER, 2025), this trajectory allows the system to remain flexible in the short term while enabling a total phase-out of unabated gas generation toward the end of the horizon.
- Coal and Oil: These technologies are assigned the most aggressive reduction paths. The limit starts at 25% and reaches linearly 100% by 2045. This reflects the high priority of the Coal Phase-Out and is well above the historical maximum reductions 15% for coal (EMBER, 2025) and 15% for oil (EMBER, 2025)), providing the model the freedom to accelerate the decommissioning of these carbon-intensive assets.
- Nuclear Power: Following the first year, a constant 10% maximum decrease is assumed. This is slightly above the historical maximum drop of 6% (EMBER, 2025), providing some operational flexibility. Importantly, unlike fossil fuels, this limit is not increased over time. This aligns with the WEO 2024 European STEPS scenario (IEA, 2024), which assumes a policy focus on decarbonizing the power sector rather than a complete phase-out of the nuclear fleet, assuming it instead as a key provider of low-carbon baseload.

6.3. Announced Pledges Scenario Modelling Inputs

Capital Cost

Table 6.42: APS Scenario Capital Cost

Capital Cost ($/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	6,600	6,350	5,100	4,950	4,800	4,650	4,500
WIND ON	1,630	1,615	1,540	1,520	1,500	1,480	1,460
WIND OFF	3,120	2,967	2,200	2,025	1,850	1,675	1,500
PV	750	702	460	428	395	363	330
BIO	4,370	4,340	4,192	4,044	3,896	3,748	3,600
GEO	5,000	5,000	5,000	5,000	5,000	5,000	5,000
RESERVOIR	3,600	3,600	3,600	3,600	3,600	3,600	3,600
ROR	3,500	3,500	3,500	3,500	3,500	3,500	3,500
CCGT	1,000	1,000	1,000	1,000	1,000	1,000	1,000
COAL	2,000	2,000	2,000	2,000	2,000	2,000	2,000
SCGT	700	700	700	700	700	700	700
PHES	2,000	2,000	2,000	2,000	2,000	2,000	2,000
BATT	300	295	270	245	220	195	170
OIL	600	600	600	600	600	600	600
COAL CCS	5,500	5,464	5,282	5,100	5,080	5,092	4,650
GAS CCS	3,100	3,077	2,964	2,850	2,767	2,683	2,600

The cost projections for the APS Scenario, reported in Table 6.42, are obtained applying the same methodological logic used in the previous scenario. The cost projection for Gas CCS and Coal CCS are sourced in the European APS Scenario in (IEA, 2025), while the cost projections for Nuclear, Wind On, Wind Off and PV are sourced in the European APS Scenario in (IEA, 2024). The overall construction of these pathways relies on linear interpolation between milestone years, as already explained in the previous scenario. Battery storage costs follow the NREL 2024 Intermediate trajectory (NREL, 2024). Conversely, the capital cost for biomass, geothermal, CCGT, coal, oil, SCGT, RoR, reservoir, and PHES remains uniform across all scenarios, as previously analysed in the STEPS Scenario.

Fixed Cost O&M

The trajectory construction follows the same logic as the one reported for the previous scenario. The fixed cost expressed as % of the Capex, reported in Table 6.33, are assumed to be uniform within all scenarios. Table 6.43 reports the Fixed O&M Costs for the different technologies in the APS Scenario.

Table 6.43: APS Scenario Fixed O&M Cost

Fixed O&M Cost (USD/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	132	127	102	99	96	93	90
WIND ON	33	32	31	30	30	30	29
WIND OFF	78	74	55	51	46	42	38
PV	10	9	6	6	5	5	4
BIO	164	163	157	152	146	141	135
GEO	175	175	175	175	175	175	175
RESERVOIR	72	72	72	72	72	72	72
ROR	70	70	70	70	70	70	70
CCGT	20	20	20	20	20	20	20
COAL	40	40	40	40	40	40	40
SCGT	19	19	19	19	19	19	19
PHES	40	40	40	40	40	40	40
OIL	17	17	17	17	17	17	17
BATT	20	19	14	13	12	11	10
COAL CCS	165	164	158	153	152	153	140
GAS CCS	78	77	74	71	69	67	65

Fuel Cost

Table 6.44: APS Scenario Fuel Cost

Fuel Cost [$/MWh]	2024	2025	2030	2035	2040	2045	2050
COAL	16.0	15.7	14.4	13.1	12.7	12.2	11.7
OIL	46.5	47.0	49.7	52.4	55.7	59.0	62.4
GAS	35.1	34.8	32.9	31.0	32.8	34.5	36.2
URANIUM	9.0	9.0	9.0	9.0	9.0	9.0	9.0
BIO	39.6	39.6	39.6	39.6	39.6	39.6	39.6

Fuel price projections for gas, coal, and oil, reported in Table 6.35, are sourced from the European Announced Pledges Scenario (APS) in (IEA, 2024). The trajectory construction follows the same logic as the one reported for the previous scenario. Conversely, fuel cost for biomass and uranium, reported in Table 6.44, remains uniform across all scenarios, as previously analysed in the STEPS scenario.

Emission Penalty

Table 6.45: APS Scenario Emission Penalty

Year	2024	2025	2030	2035	2040	2045	2050
Emission Penalty [$/Ton]	75	83	124	165	177	188	200

Emission penalty projections, reported in Table 6.45, are sourced from the WEO 2024 European APS scenario (IEA, 2024). The trajectory construction follows the same logic as reported for the previous STEPS scenario.

Capital Cost Of Storage

Table 6.46: APS Scenario Capital Cost of Storage

Capital Cost of Storage ($/KWh)	2024	2025	2030	2035	2040	2045	2050
BATT	288	283	258	233	207	182	157

Capital costs for storage batteries, reported in Table 6.46, are sourced from the NREL 2024 Intermediate scenario (NREL, 2024). The trajectory construction follows the same logic as the one reported for the STEPS scenario.

Specified Annual Demand

Table 6.47: APS Scenario Specified Annual Demand

Specified Annual Demand [TWh]	2024	2025	2030	2035	2040	2045	2050
ELC_SERVICE	1,115.8	1,149.3	1,316.4	1,483.5	1,650.6	1,817.7	1,984.8
ELC_RES	1,011.2	1,021.4	1,072.3	1,123.2	1,174.1	1,225.0	1,275.9
ELC_IND	1,255.3	1,291.6	1,472.7	1,653.9	1,835.1	2,016.2	2,197.4
ELC_MOB	104.6	163.3	456.7	750.1	1,043.5	1,336.9	1,630.3
Aggregated Electricity	3,487.0	3,625.5	4,318.1	5,010.7	5,703.2	6,395.8	7,088.4

For the APS Scenario, since the WEO 2025 does not include this specific scenario projection, the 2050 electricity demand is reconstructed by applying a scaling factor to the Electricity Demand for the European STEPS Scenario of WEO 2025.

A coefficient of 1.2 is derived as the ratio between the 2050 Total Electricity Generation in Europe in the WEO 2024 Announced Pledges Scenario and the 2050 Total Electricity Generation in Europe in the WEO 2024 Stated Policies Scenario, both sourced in (IEA, 2024). This coefficient of 1.2 is then multiplied by the 2050 Electricity Demand for the European STEPS Scenario of WEO 2025 sourced in (IEA, 2025). It is therefore assumed that electricity demand grows by the same factor as electricity generation, under the assumption that transmission and distribution (T&D) losses remain constant in percentage terms.

The subsequent construction of the demand trajectories for the four sectors, reported in Table 6.47, follows the same methodology previously described in the STEPS scenario.

Total Annual Max Capacity Investment

Table 6.48: APS Scenario Total Annual Max Capacity Investment

Total Max Capacity Inv. [GW]	2024	2025	2026	2027	2028	2029	2030	2031	2035	2040	2045	2050
PHES	-	3	3	3	3	3	3	2	2	2	2	2
BATT	1	15	30	35	50	50	50	50	50	70	70	70
COAL CCS	-	1	1	1	1	1	1	1	1	1	1	1
GAS CCS	-	2	2	2	2	2	2	3	5	5	5	5
WIND ON	-	40	40	40	40	40	40	40	40	40	40	40
WIND OFF	-	30	30	30	30	30	30	40	50	50	50	50
PV	-	110	110	110	110	110	110	110	110	110	110	110
BIO	-	5	5	5	5	5	5	5	5	5	5	5
RESERVOIR	-	-	-	-	-	-	-	-	-	-	-	-
GEO	-	-	-	-	-	-	-	-	-	-	-	-
NUC	-	3	3	3	4	4	5	5	7	8	10	10
SCGT	-	2	2	2	2	2	2	2	2	2	2	1
COAL	-	-	-	-	-	-	-	-	-	-	-	-
OIL	-	-	-	-	-	-	-	-	-	-	-	-
CCGT	-	6	6	6	5	5	5	3	3	3	2	1

In the APS Scenario the model assumes a more rapid and extensive deployment of key technologies compared to the STEPS scenario, as reported in Table 6.48:

- Carbon Capture and Storage (CCS): A larger deployment is assumed, though it remains capped by the technical and economic constraints previously discussed.
- Renewables (PV & Wind): Mass expansion begins as early as 2025, driven by the EU targets of 42% share of renewables by 2030 and the Net-Zero Industry Act (NZIA), which aims to triple the EU's manufacturing capacity for key net-zero technologies by 2030, as sourced in (IEA, 2024). Based on current estimates of ~300 GW for Solar PV (EMBER, 2025) and ~230 GW for Wind (EMBER, 2025) in 2024 in European Union, achieving the NZIA objectives would require reaching approximately 1,600 GW of combined capacity by 2030. This translates to an annual growth rate of roughly +200 GW (PV + Wind), justifying the higher Total Annual Max Capacity Investment limits in this scenario. In addition, toward the end of the period, the investment limit for Offshore Wind is assumed to exceed that of Onshore Wind, reflecting the steeper cost reductions and strategic focus on large-scale maritime projects, as reported in (IEA, 2024).
- Nuclear & Gas: Nuclear power follows a gradual development trend characterized by long lead times. Compared to the STEPS scenario, a higher total maximum capacity investment has been assumed toward the end of the planning horizon. However, this divergence from the STEPS pathway is not as pronounced as that observed for renewable technologies, primarily due to three factors: first, a lower strategic push compared to renewables, despite a strong renewed interest in nuclear energy (European Commission , 2025); second, the significantly longer technical construction periods; and finally,

the European trend that prioritizes in the short run the long-term operation and lifetime extension of existing plants over the development of new projects (Carbon Free Europe, 2025). Conversely, the growth profile for Natural Gas is more restricted to align with the APS policy objective of decarbonizing the EU and UK power sectors by 2035 and phasing out Russian gas by 2030, as sourced in (IEA, 2024). Despite these decarbonization goals, a mandatory drastic phase-out of gas is not imposed. As the model represents Continental Europe, it accounts for the reality that several countries will likely remain dependent on gas through 2050.

Technology Annual Activity Increase Limit

Table 6.49: APS Scenario Annual Activity Increase Limit

Max Increase [%] of Production	2024	2025	2030	2035	2040	2045	2050
WIND ON	25%	30%	30%	30%	20%	10%	10%
WIND OFF	25%	30%	35%	35%	30%	20%	20%
PV	25%	30%	30%	30%	20%	10%	10%
ROR	0%	0%	0%	0%	0%	0%	0%
BIO	5%	5%	10%	10%	10%	10%	10%
NUC	5%	5%	10%	10%	10%	10%	10%
CCGT	10%	10%	10%	10%	10%	10%	5%
SCGT	10%	10%	10%	10%	10%	10%	5%

Regarding the TechnologyActivityIncreaseByModeLimit for the APS scenario (Table 6.49) the values are adjusted from the STEPS to reflect the scenario's higher climate ambition. For Gas-fired power, a lower annual increase limit is assumed compared to the one used in the STEPS scenario, as reported in Table 6.40. Furthermore, this limit is progressively reduced toward the end of the simulation, by 2046 onward, to symbolize the transition toward a more stringent decarbonization path and a reduced reliance on gas, in line with the scenario’s environmental targets and policies, as reported in (IEA, 2024).

Technology Annual Activity Decrease Limit

Table 6.50: APS Scenario Annual Activity Decrease Limit

Max Decrease [%] of Production	2024	2025	2030	2035	2040	2045	2050
BIO	5%	5%	5%	5%	5%	5%	5%
NUC	5%	10%	10%	10%	10%	10%	10%
CCGT	15%	18%	35%	51%	67%	84%	100%
COAL	25%	29%	46%	64%	82%	100%	100%
OIL	25%	29%	46%	64%	82%	100%	100%
SCGT	15%	18%	35%	51%	67%	84%	100%

Table 6.50 represents the assumed Annual Activity Decrease Limit in the APS Scenario. It is assumed that the decrease limits remain constant relative to the STEPS Scenario, as reported in Table 6.41. In fact, the higher climate ambition of the APS scenario is already reflected by the constraints on increase limits and total annual

maximum capacity, as well as by the assumption of greater CAPEX cost reductions for green technologies.

6.4. Net Zero Emission 2050 Scenario Modelling Inputs

Capital Cost

Table 6.51: NZE Scenario Capital Cost

Capital Cost ($/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	6,600	6,350	5,100	4,950	4,800	4,650	4,500
WIND ON	1,630	1,613	1,530	1,508	1,485	1,463	1,440
WIND OFF	3,120	2,957	2,140	1,965	1,790	1,615	1,440
PV	750	702	460	425	390	355	320
BIO	4,370	4,340	4,192	4,044	3,896	3,748	3,600
GEO	5,000	5,000	5,000	5,000	5,000	5,000	5,000
RESERVOIR	3,600	3,600	3,600	3,600	3,600	3,600	3,600
ROR	3,500	3,500	3,500	3,500	3,500	3,500	3,500
CCGT	1,000	1,000	1,000	1,000	1,000	1,000	1,000
COAL	2,000	2,000	2,000	2,000	2,000	2,000	2,000
SCGT	700	700	700	700	700	700	700
PHES	2,000	2,000	2,000	2,000	2,000	2,000	2,000
OIL	600	600	600	600	600	600	600
BATT	300	293	257	222	186	151	115
COAL CCS	5,500	5,386	4,818	4,250	4,183	4,117	4,050
GAS CCS	3,100	3,032	2,691	2,350	2,300	2,250	2,200

The cost projections for the NZE Scenario, reported in Table 6.51, are obtained applying the same methodological logic used in the previous scenarios. The cost projection for Gas CCS and Coal CCS are sourced in the European NZE Scenario in (IEA, 2025), while the cost projections for Nuclear, Wind On, Wind Off and PV are sourced in the European NZE Scenario in (IEA, 2024). The overall construction of these pathways relies on linear interpolation between milestone years, as already explained in the previous scenarios. Conversely, the capital cost for biomass, geothermal, CCGT, coal, oil, SCGT, RoR, reservoir, and PHES remains uniform across all scenarios, as previously analysed in the STEPS and APS scenario.

Battery storage costs follow the NREL 2024 Advanced trajectory (NREL, 2024).

Fixed Cost O&M

Table 6.52: NZE Scenario Fixed O&M Cost

Fixed O&M Cost ($/KW)	2024	2025	2030	2035	2040	2045	2050
NUC	132.0	127.0	102.0	99.0	96.0	93.0	90.0
WIND ON	32.6	32.3	30.6	30.2	29.7	29.3	28.8
WIND OFF	78.0	73.9	53.5	49.1	44.8	40.4	36.0
PV	10.1	9.5	6.2	5.7	5.3	4.8	4.3
BIO	163.9	162.8	157.2	151.7	146.1	140.6	135.0
GEO	175.0	175.0	175.0	175.0	175.0	175.0	175.0
RESERVOIR	72.0	72.0	72.0	72.0	72.0	72.0	72.0
ROR	70.0	70.0	70.0	70.0	70.0	70.0	70.0
CCGT	20.0	20.0	20.0	20.0	20.0	20.0	20.0
COAL	40.0	40.0	40.0	40.0	40.0	40.0	40.0
SCGT	19.3	19.3	19.3	19.3	19.3	19.3	19.3
PHES	40.0	40.0	40.0	40.0	40.0	40.0	40.0
OIL	16.5	16.5	16.5	16.5	16.5	16.5	16.5
BATT	20.0	18.9	13.2	12.3	11.4	10.5	9.6
COAL CCS	165.0	161.6	144.5	127.5	125.5	123.5	121.5
GAS CCS	77.5	75.8	67.3	58.8	57.5	56.3	55.0

Table 6.52 reports the Fixed O&M Costs for the different technologies in the NZE Scenario.

The trajectory construction follows the same logic as the one reported for the previous scenarios. The fixed cost expressed as % the Capex, reported in Table 6.33, are assumed to be uniform within all scenarios.

Fuel Cost

Table 6.53: NZE Scenario Fuel Cost

Fuel Cost [$/MWh]	2024	2025	2030	2035	2040	2045	2050
COAL	16.0	15.2	10.9	6.7	6.3	6.0	5.6
OIL	46.5	44.0	31.7	19.4	17.8	16.3	14.7
GAS	35.1	33.3	23.8	14.3	14.1	13.9	13.6
URANIUM	9.0	9.0	9.0	9.0	9.0	9.0	9.0
BIO	39.6	39.6	39.6	39.6	39.6	39.6	39.6

Fuel price projections for gas, coal, and oil, reported in Table 6.53, are sourced in the European Net Zero Emission 2050 Scenario in (IEA, 2024). The trajectory construction follows the same logic as the one reported for the previous scenario. Conversely, fuel cost for biomass and uranium, reported in Table 6.53, remains uniform across all scenarios, as analysed in the previous scenarios.

Emission Penalty

Table 6.54: NZE Scenario Emission Penalty

Year	2024	2025	2030	2035	2040	2045	2050
Emission Penalty [$/Tton]	75	85	132	180	203	227	250

Emission penalty projections, reported in Table 6.54, are sourced in the European NZE scenario in (IEA, 2024). The trajectory construction follows the same logic as the one reported for the previous scenarios.

Annual Emission Limit

Table 6.55: NZE Scenario Annual Emission Limit

Year	2024	2025	2030	2035	2040	2045	2050
Annual Emission Limit [Mton]	680	654	523	392	262	131	0

As the Net Zero Emissions (NZE) scenario is a normative scenario, designed to meet a specific end-target an exogenous emission limit curve is introduced as a primary constraint, as reported in Table 6.55. This trajectory starts from the CO_2 emission levels of the 2024 Reference Energy System (RES) and decreases linearly to reach zero emissions by 2050. This approach forces the model to identify the technological mix required to achieve total decarbonization by 2050.

Capital Cost of Storage

Table 6.56: NZE Scenario Capital Cost of Storage

Capital Cost of Storage ($/KWh)	2024	2025	2030	2035	2040	2045	2050
BATT	288	282	251	221	190	160	130

Capital costs for storage batteries, reported in Table 6.56, are sourced in the NREL 2024 Advanced scenario (NREL, 2024). The trajectory construction follows the same logic as the one reported for the STEPS scenario.

Specified Annual Demand

Table 6.57: NZE Scenario Specified Annual Demand

Specified Annual Demand [TWh]	2024	2025	2030	2035	2040	2045	2050
ELC_SERVICE	1,115.8	1,155.5	1,354.0	1,552.5	1,751.0	1,949.5	2,148.0
ELC_RES	1,011.2	1,025.4	1,096.5	1,167.6	1,238.7	1,309.8	1,380.9
ELC_IND	1,255.3	1,298.5	1,514.4	1,730.4	1,946.3	2,162.2	2,378.1
ELC_MOB	104.6	168.4	487.6	806.8	1,126.0	1,445.2	1,764.4
Aggregated Electricity	3,487.0	3,647.9	4,452.6	5,257.3	6,062.0	6,866.7	7,671.4

For the Net Zero Emissions (NZE) scenario, the 2050 electricity demand for Europe is reconstructed through a comparative scaling methodology. This approach is necessitated by the absence of any region-specific NZE projections for Electricity Generating and Demand for Europe in both the IEA WEO 2024 and WEO 2025 reports.

The estimation is conducted according to the following analytical steps:

- Firstly, the growth coefficient for global electricity generation is determined by calculating the ratio between the 2050 NZE Electricity Generation and the

2024 baseline from the WEO 2024, sourced in (IEA, 2024). This yielded a global growth factor of 2.56.

- Then the same calculation is applied to the global APS (Announced Pledges) and STEPS (Stated Policies) scenarios, sourcing in (IEA, 2024), resulting in growth factors of 1.9 and 1.85, respectively. These scenario dependent values represent the global growth factor for electricity generation up to 2050, starting with the 2024 baseline.
- When performing the same calculation specifically for the European region using APS and STEPS data, sourcing in (IEA, 2024), the growth factors for the electricity generation up to 2050 are found to be 1.7 and 1.6. By comparing these to the global figures, it is determined that Europe's growth rate consistently represents approximately 85% of the global trend.
- Consequently, the global NZE growth factor of 2.56 is scaled by this 0.85 regional multiplier, resulting in a specific European coefficient of 2.2. Therefore, the growth factor for European electricity generation by 2050 is indirectly estimated. This coefficient is then applied to the 2024 European electricity demand baseline, sourced in (IEA, 2025), to estimate the total demand for 2050. This projection assumes that electricity generation and demand are directly proportional. Specifically, it assumes that if generation increases by a factor of 2.2, demand follows the same trajectory, under the assumption that network losses (expressed as a percentage) remain constant through 2050.

Successively, consistent with the methodology described for the STEPS scenario, the resulting total demand is then disaggregated across the four primary consumption sectors to build the final annual trajectories up to 2050, as reported in Table 6.57.

Total Annual Max Capacity Investment

Table 6.58: NZE Scenario Total Annual Max Capacity Investment

Total max capacity inv. [GW]	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2040	2045	2050
PHES	-	3	3	3	3	3	3	2	2	2	2	2	2	2	2
BATT	1	15	30	35	50	70	80	80	100	100	100	120	120	150	150
COAL CCS	-	1	1	1	1	1	1	1	1	1	1	1	1	1	1
GAS CCS	-	3	3	4	5	5	5	5	5	5	5	5	5	5	5
WIND ON	-	40	40	40	40	40	50	50	50	50	50	60	60	60	60
WIND OFF	-	30	30	30	30	30	40	50	50	50	50	60	60	70	70
PV	-	110	110	110	110	110	120	120	120	120	120	130	130	130	130
BIO	-	5	5	5	5	5	5	5	5	5	5	5	7	7	7
RESERVOIR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
GEO	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NUC	-	5	5	5	5	5	5	5	5	5	5	7	8	10	12
SCGT	-	2	2	2	2	2	2	2	2	2	2	2	-	-	-
COAL	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
OIL	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CCGT	-	6	6	6	6	6	6	6	5	3	2	2	-	-	-

In the NZE scenario, an accelerated deployment of renewable energy, nuclear power, and battery storage systems is assumed, as reported in Table 6.58.

Technology Annual Activity Increase Limit

Table 6.59: NZE Scenario Annual Activity Increase Limit

Max Increase [%] of Production	2024	2025	2030	2035	2040	2045	2050
WIND ON	30%	30%	30%	30%	30%	30%	30%
WIND OFF	40%	40%	40%	40%	40%	30%	30%
PV	30%	30%	30%	30%	30%	30%	30%
ROR	0%	0%	0%	0%	0%	0%	0%
BIO	15%	15%	15%	15%	15%	15%	15%
NUC	10%	10%	10%	10%	10%	10%	10%
CCGT	10%	10%	10%	10%	10%	10%	5%
SCGT	10%	10%	10%	10%	10%	10%	5%

The NZE (Net Zero Emissions) scenario assumes a higher annual activity increase limit for renewable energy sources, nuclear power, and biomass, as reported in Table 6.59. This adjustment reflects the rapid and large-scale deployment of renewable energy and low-carbon dispatchable sources required to meet the strict decarbonization targets by 2050.

Technology Annual Activity Decrease Limit

Table 6.60: NZE Scenario Annual Activity Decrease Limit

Max Decrease [%] of Production	2024	2025	2030	2035	2040	2045	2050
BIO	5%	5%	5%	5%	5%	5%	5%
NUC	5%	10%	10%	10%	10%	10%	10%
CCGT	35%	38%	50%	63%	75%	88%	100%
COAL	50%	52%	64%	76%	88%	100%	100%
OIL	50%	52%	64%	76%	88%	100%	100%
SCGT	35%	38%	50%	63%	75%	88%	100%

The NZE (Net Zero Emissions) scenario assumes a higher annual activity decrease limits for carbon-intensive technologies, as reported in Table 6.60. This provides the model with greater flexibility to implement a more rapid and drastic reduction of fossil-fuel generation, ensuring alignment with the stringent decarbonization targets of the NZE scenario.

6.5. Conclusion of the Chapter

Following a comprehensive analysis of the input parameters across the three modelled pathways, the Announced Pledges Scenario (APS) emerges as the most plausible central trajectory for the European energy transition. While the Stated Policies Scenario (STEPS) arguably provides a conservative outlook that may underestimate the rapid momentum of recent climate commitments, the Net Zero Emissions (NZE) scenario represents an extremely ambitious normative pathway that assumes perfect policy implementation and no friction in global supply chains.

Consequently, the APS serves as a balanced middle-ground; it accounts for the full implementation of all national climate targets, aligning political ambition with a more realistic, albeit accelerated, pace of technological and structural change. This makes it the most robust baseline for evaluating the systemic implications of the Continental European power sector's evolution.

7 Results, Analysis, and Critical Discussion

7.1. Stated Policies Scenario (STEPS)

The following sections provide a detailed analysis of the primary outputs generated by the STEP scenario simulation. The discussion focuses specifically on the evolution of New Capacity and Total Capacity, the dynamics of Electricity Production, and the trajectory of CO_2 emissions generated by the system throughout the modelled time horizon.

New Capacity, Total Capacity and Production Analysis

Table 7.1: STEPS Scenario New Installed Capacity

New Capacity [GW]	BATT	PHES	BIO	GAS CCS	COAL CCS	ROR	CCGT	SCGT	NUC	PV	WIND OFF	WIND ON
2024	0.75	-	-	-	-	-	-	-	-	-	-	-
2025	-	-	-	0.43	-	0.15	10.00	4.00	-	70.00	-	20.00
2026	-	-	-	-	-	0.15	10.00	4.00	-	70.00	-	20.00
2027	0.07	1.23	-	0.99	-	0.15	10.00	4.00	-	70.00	-	25.00
2028	-	3.00	-	0.82	-	-	10.00	4.00	-	70.00	3.88	25.00
2029	0.22	3.00	-	-	-	-	10.00	4.00	-	70.00	11.87	25.00
2030	-	3.00	-	-	-	-	10.00	4.00	-	70.00	20.16	25.00
2031	1.57	2.00	-	-	-	-	8.00	4.00	-	80.00	25.94	30.00
2032	2.04	2.00	-	2.00	-	-	8.00	4.00	-	80.00	26.40	30.00
2033	2.12	2.00	-	2.00	-	-	8.00	4.00	-	80.00	28.93	30.00
2034	2.49	2.00	-	2.00	-	-	8.00	4.00	-	80.00	30.00	30.00
2035	6.32	2.00	-	3.00	-	-	6.00	4.00	-	90.00	40.00	10.57
2036	10.37	2.00	-	3.00	-	-	6.00	4.00	-	90.00	40.00	-
2037	10.95	2.00	-	3.00	-	-	6.00	4.00	-	90.00	40.00	-
2038	11.28	2.00	-	3.00	-	-	6.00	4.00	-	90.00	40.00	-
2039	20.01	2.00	-	3.00	-	-	6.00	4.00	4.08	89.80	15.79	-
2040	7.48	2.00	-	3.00	-	-	6.00	4.00	8.00	42.11	40.00	-
2041	7.85	2.00	-	3.00	-	-	6.00	4.00	8.00	65.41	40.00	-
2042	8.26	2.00	-	3.00	-	-	6.00	4.00	8.00	94.08	40.00	-
2043	8.61	2.00	-	3.00	-	-	6.00	4.00	8.00	100.00	40.00	-
2044	11.45	2.00	-	3.00	-	-	6.00	4.00	8.00	100.00	40.00	-
2045	12.16	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-
2046	12.37	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-
2047	11.49	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-
2048	9.92	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-
2049	8.51	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-
2050	16.83	2.00	-	3.00	-	-	5.00	3.00	8.00	100.00	40.00	-

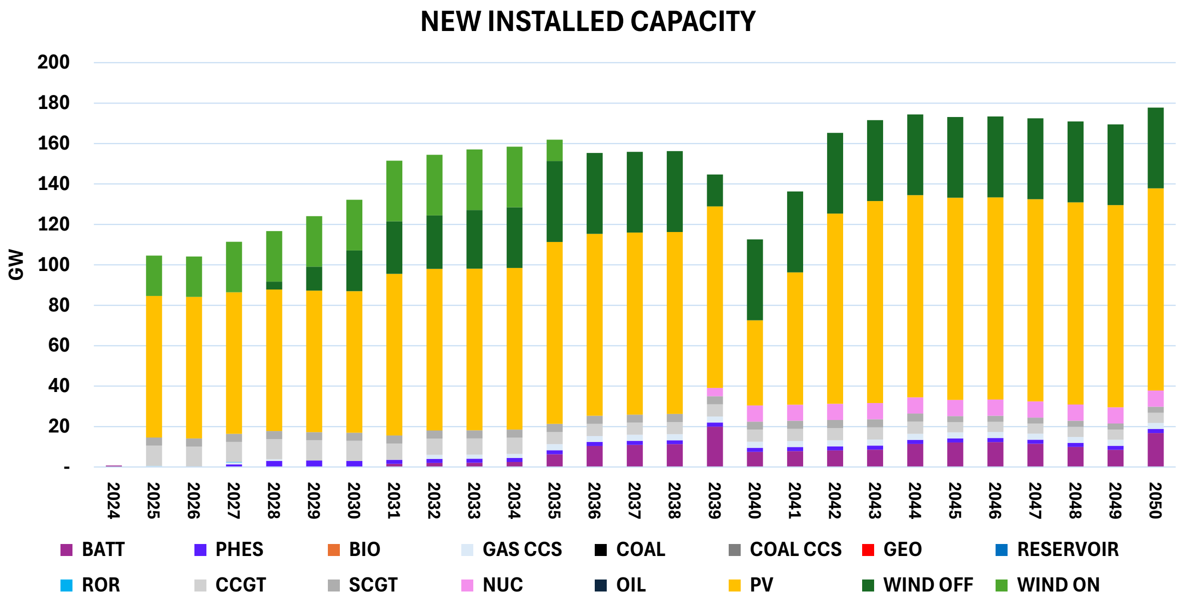

Figure 7.1: STEPS Scenario New Installed Capacity

Table 7.2: STEPS Scenario Total Installed Capacity

Total Capacity [GW]	BATT	PHES	BIO	GAS CCS	COAL	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	11.8	28.9	45.1	-	152.0	73.2	227.9	76.0	116.1	29.5	364.0	35.7	246.2
2025	11.8	28.9	45.1	0.4	147.8	73.3	237.9	79.2	116.1	29.2	434.0	35.7	266.2
2026	11.8	28.9	45.1	0.4	141.6	73.5	247.7	82.0	116.1	28.7	504.0	35.7	286.2
2027	11.9	30.1	45.1	1.4	133.2	73.6	257.4	84.6	116.1	28.2	573.9	35.7	311.2
2028	11.9	33.1	45.1	2.2	122.5	73.6	266.9	86.7	116.1	27.4	643.9	39.6	336.2
2029	12.0	36.1	45.1	2.2	109.5	73.6	276.1	88.3	116.1	26.5	713.9	51.4	361.2
2030	12.0	39.1	45.1	2.2	94.8	73.6	284.8	89.4	116.0	25.4	783.8	71.6	386.2
2031	13.5	41.1	45.1	2.2	79.2	73.6	290.8	90.0	116.0	24.1	863.7	97.5	416.2
2032	15.3	43.1	45.0	4.2	63.6	73.6	295.8	90.1	115.8	22.6	943.5	123.9	446.2
2033	16.9	45.1	44.9	6.2	48.9	73.6	299.5	89.8	115.7	20.9	1,023.2	152.9	476.2
2034	18.5	47.1	44.8	8.2	35.9	73.6	301.6	89.0	115.4	19.0	1,102.8	182.9	506.1
2035	23.6	49.1	44.7	11.2	25.1	73.6	299.8	88.0	115.0	17.1	1,192.1	222.9	516.6
2036	32.3	51.1	44.4	14.2	16.7	73.6	295.8	86.9	114.4	15.1	1,281.2	262.9	516.4
2037	41.5	53.1	44.1	17.2	10.6	73.6	289.7	85.7	113.5	13.1	1,369.9	302.9	516.0
2038	51.2	55.1	43.6	20.2	6.3	73.6	281.5	84.7	112.2	11.2	1,458.1	342.9	515.2
2039	69.2	57.1	43.0	23.2	3.6	73.6	271.4	84.0	114.6	9.3	1,545.5	358.6	513.8
2040	75.8	59.1	42.1	26.2	1.9	73.6	260.1	83.6	120.4	7.6	1,584.4	398.6	511.2
2041	83.2	61.1	41.0	29.2	1.0	73.6	248.0	83.7	125.6	6.1	1,645.6	438.6	506.9
2042	91.1	63.1	39.6	32.2	0.5	73.6	235.9	84.3	130.1	4.8	1,734.2	478.6	500.3
2043	99.6	65.1	38.0	35.2	0.2	73.6	224.6	85.5	133.8	3.7	1,827.5	518.6	490.8
2044	110.8	67.1	36.0	38.2	0.1	73.6	214.5	87.1	136.7	2.8	1,919.2	558.6	477.7
2045	123.0	69.1	33.7	41.2	0.0	73.6	205.3	88.2	138.9	2.0	2,009.3	598.5	461.0
2046	133.8	71.1	31.2	44.2	0.0	73.6	198.2	89.7	140.4	1.4	2,097.6	638.3	440.8
2047	143.2	73.1	28.5	47.2	0.0	73.6	193.2	91.6	141.3	1.0	2,184.1	677.8	418.0
2048	151.0	75.1	25.5	50.2	-	73.6	190.4	93.8	141.8	0.7	2,268.9	716.9	393.7
2049	157.0	77.1	22.6	53.2	-	73.6	189.5	96.2	142.1	0.5	2,352.1	755.4	369.4
2050	167.5	79.1	19.6	56.2	-	73.6	190.2	94.8	142.5	0.3	2,433.8	793.0	326.5

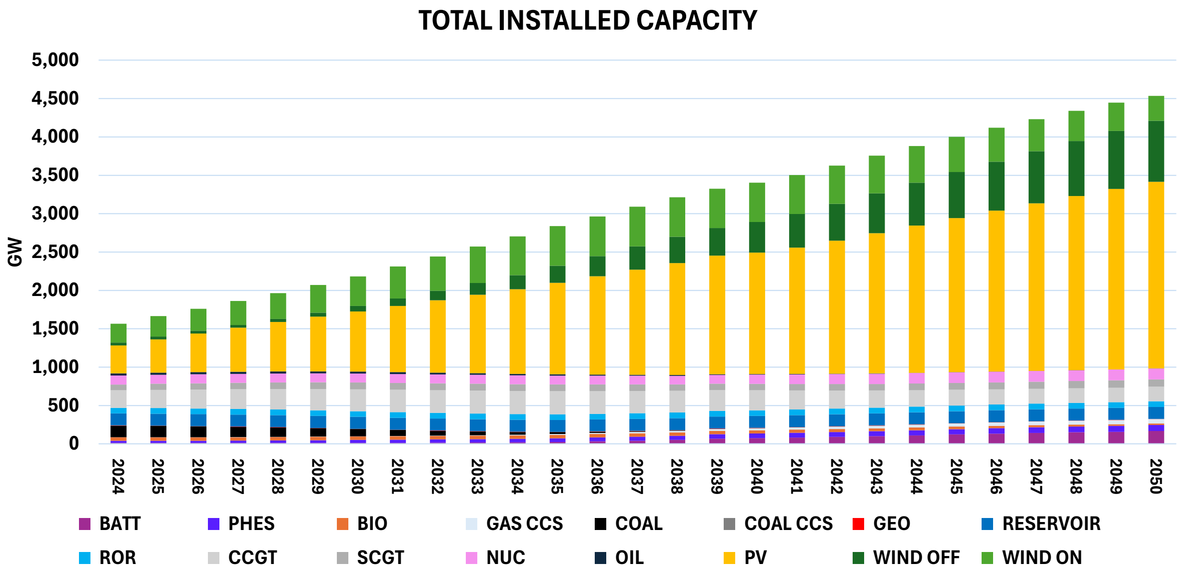

Figure 7.2: STEPS Scenario Total Installed Capacity

Table 7.3: STEPS Scenario Total Net Electricity Production

Production [TWh]	BATT	PHES	BIO	GAS CCS	COAL	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	2.5	2.2	191.9	-	434.0	24.2	374.0	293.2	654.4	34.4	742.0	102.4	384.9	99.9	519.2
2025	0.5	2.0	182.3	3.4	325.5	24.2	374.0	293.7	752.5	29.3	762.8	76.8	458.9	99.9	561.3
2026	3.3	2.4	173.2	3.4	231.1	24.2	374.0	294.3	831.6	24.0	800.9	54.5	532.9	99.9	603.5
2027	3.6	9.7	164.5	11.2	157.2	24.2	374.0	294.9	893.7	18.7	813.6	37.1	606.9	99.9	656.2
2028	9.2	19.1	156.3	17.6	100.6	24.2	374.0	294.9	882.7	21.5	864.3	23.7	680.9	110.8	706.5
2029	13.9	62.3	148.5	17.6	61.4	24.2	374.0	294.9	902.8	24.8	864.1	14.5	754.9	144.0	749.0
2030	13.2	84.5	141.1	17.6	50.0	24.2	374.0	294.9	864.9	28.5	863.8	8.3	828.9	187.2	800.5
2031	14.5	89.8	134.0	11.8	36.2	24.2	374.0	294.6	822.4	32.7	837.7	4.5	913.3	252.7	849.8
2032	11.2	80.9	127.3	18.3	22.1	24.2	374.0	294.1	795.1	36.0	779.0	2.2	988.9	339.1	887.1
2033	10.9	87.3	120.9	25.2	10.2	24.2	374.0	293.5	765.1	37.2	726.3	2.1	1,076.2	421.9	915.1
2034	13.0	89.5	114.9	33.3	5.1	24.2	374.0	292.9	732.5	34.3	670.7	2.0	1,148.2	505.3	957.8
2035	22.1	93.9	109.2	45.4	3.4	24.2	374.0	292.3	695.9	30.8	617.8	2.0	1,247.1	596.8	961.9
2036	38.9	101.0	103.7	57.5	2.2	24.1	374.0	291.7	667.5	28.5	571.7	1.9	1,301.7	714.2	968.1
2037	58.9	110.8	98.5	69.6	1.4	24.1	374.0	291.1	639.1	27.2	524.4	1.7	1,391.5	833.5	939.1
2038	76.8	121.5	93.6	81.0	0.8	24.0	374.0	290.5	611.0	26.9	477.6	1.4	1,463.9	922.0	955.4
2039	108.7	122.5	88.9	91.1	0.6	24.0	374.0	290.0	598.6	28.3	467.7	1.3	1,569.4	976.8	918.6
2040	114.5	112.4	84.5	102.7	0.3	23.9	373.3	289.4	561.0	29.8	489.8	1.0	1,606.6	1,079.5	887.7
2041	127.1	100.8	80.2	114.3	0.2	23.9	372.5	288.8	520.8	31.3	508.7	0.8	1,667.7	1,167.0	853.9
2042	144.4	86.8	76.2	124.7	0.1	23.8	371.8	288.2	477.9	32.2	522.1	0.7	1,730.6	1,228.7	852.9
2043	153.0	71.8	72.4	133.3	0.0	23.8	371.0	287.7	440.8	33.5	534.7	0.6	1,782.7	1,350.4	798.2
2044	166.2	60.7	68.8	142.8	0.0	23.7	370.3	287.1	409.2	35.0	544.4	0.5	1,865.9	1,419.6	762.5
2045	183.5	60.6	65.4	153.8	0.0	23.7	369.6	286.5	382.2	36.6	551.4	0.4	1,912.0	1,519.4	733.7
2046	191.5	63.6	62.1	165.4	0.0	23.6	368.8	285.9	360.6	38.5	555.9	0.3	1,888.3	1,713.6	675.3
2047	214.1	67.9	59.0	177.6	0.0	23.6	368.1	285.4	344.8	40.4	558.1	0.2	2,027.9	1,745.6	614.4
2048	223.1	72.2	56.0	189.6	-	23.5	367.3	284.8	333.2	42.5	559.0	0.1	2,101.4	1,825.1	567.3
2049	213.3	76.7	53.2	201.0	-	23.5	366.6	284.2	324.6	44.6	559.2	0.2	2,139.5	1,908.6	547.5
2050	274.1	75.6	50.6	216.2	-	23.5	365.9	283.6	326.8	45.8	560.4	0.1	2,294.1	1,974.6	420.5

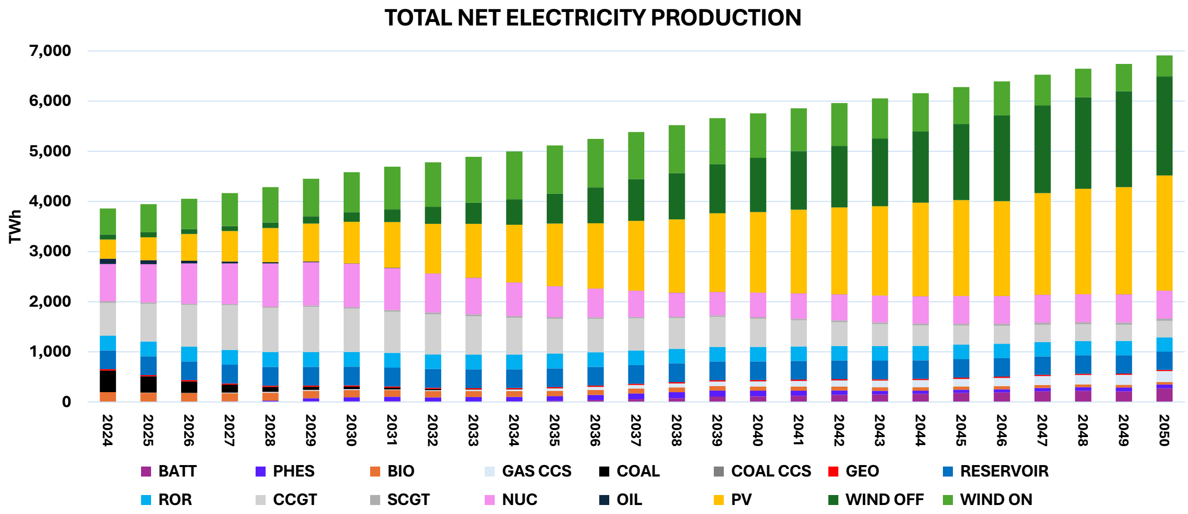

Figure 7.3: STEPS Scenario Total Net Electricity Production

Table 7.4: STEPS Scenario Capacity Factor

Capacity factor	BIO	GAS CCS	COAL	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	0.49	-	0.33	0.81	0.27	0.46	0.33	0.05	0.73	0.40	0.12	0.32	0.24
2025	0.46	0.90	0.25	0.81	0.27	0.46	0.36	0.04	0.75	0.30	0.12	0.32	0.24
2026	0.44	0.90	0.19	0.81	0.27	0.46	0.38	0.03	0.79	0.22	0.12	0.32	0.24
2027	0.42	0.90	0.13	0.81	0.27	0.46	0.40	0.03	0.80	0.15	0.12	0.32	0.24
2028	0.40	0.90	0.09	0.81	0.27	0.46	0.38	0.03	0.85	0.10	0.12	0.32	0.24
2029	0.38	0.90	0.06	0.81	0.27	0.46	0.37	0.03	0.85	0.06	0.12	0.32	0.24
2030	0.36	0.90	0.06	0.81	0.27	0.46	0.35	0.04	0.85	0.04	0.12	0.30	0.24
2031	0.34	0.60	0.05	0.81	0.27	0.46	0.32	0.04	0.82	0.02	0.12	0.30	0.23
2032	0.32	0.49	0.04	0.81	0.27	0.46	0.31	0.05	0.77	0.01	0.12	0.31	0.23
2033	0.31	0.46	0.02	0.81	0.27	0.45	0.29	0.05	0.72	0.01	0.12	0.32	0.22
2034	0.29	0.46	0.02	0.81	0.27	0.45	0.28	0.04	0.66	0.01	0.12	0.32	0.22
2035	0.28	0.46	0.02	0.81	0.27	0.45	0.27	0.04	0.61	0.01	0.12	0.31	0.21
2036	0.27	0.46	0.01	0.81	0.27	0.45	0.26	0.04	0.57	0.01	0.12	0.31	0.21
2037	0.26	0.46	0.01	0.81	0.27	0.45	0.25	0.04	0.53	0.01	0.12	0.31	0.21
2038	0.24	0.46	0.01	0.81	0.27	0.45	0.25	0.04	0.49	0.01	0.11	0.31	0.21
2039	0.24	0.45	0.02	0.80	0.27	0.45	0.25	0.04	0.47	0.02	0.12	0.31	0.20
2040	0.23	0.45	0.02	0.80	0.27	0.45	0.25	0.04	0.46	0.02	0.12	0.31	0.20
2041	0.22	0.45	0.02	0.80	0.27	0.45	0.24	0.04	0.46	0.02	0.12	0.30	0.19
2042	0.22	0.44	0.02	0.80	0.27	0.45	0.23	0.04	0.46	0.02	0.11	0.29	0.19
2043	0.22	0.43	0.02	0.80	0.27	0.45	0.22	0.04	0.46	0.02	0.11	0.30	0.19
2044	0.22	0.43	0.02	0.80	0.27	0.45	0.22	0.05	0.45	0.02	0.11	0.29	0.18
2045	0.22	0.43	0.02	0.80	0.27	0.44	0.21	0.05	0.45	0.02	0.11	0.29	0.18
2046	0.23	0.43	0.02	0.79	0.27	0.44	0.21	0.05	0.45	0.02	0.10	0.31	0.17
2047	0.24	0.43	0.02	0.79	0.27	0.44	0.20	0.05	0.45	0.02	0.11	0.29	0.17
2048	0.25	0.43	-	0.79	0.27	0.44	0.20	0.05	0.45	0.02	0.11	0.29	0.16
2049	0.27	0.43	-	0.79	0.27	0.44	0.20	0.05	0.45	0.04	0.10	0.29	0.17
2050	0.29	0.44	-	0.79	0.27	0.44	0.20	0.06	0.45	0.02	0.11	0.28	0.15

From the analysis of the output related to New Capacity in the STEPS scenario (Table 7.1 and Figure 7.1), it emerges that the model does not invest in new technologies for coal, oil, geothermal (Geo), and large hydroelectric reservoirs. This behaviour is consistent with the imposed Total Annual Max Capacity Investment constraint of zero, which reflects two primary motivations: the aim to proceed with the phase-out of coal and more carbon-intensive technologies such as oil, and the limited availability in Europe of new suitable sites for geothermal resource and new hydroelectric reservoirs.

In the initial year of the simulation (2024), the model installed approximately 0.75 GW of batteries. This dynamic is enabled by a specific model configuration: a zero Total Annual Max Capacity Investment constraint is imposed for all production technologies for the year 2024, with the aim of forcing the system to maintain an installed capacity configuration exactly linked to the calibrated RES benchmark. The only exception is deliberately reserved for electrochemical storage to provide the solver a margin of technical flexibility to respect balance constraints and satisfy electricity demand, thereby mitigating the impact of intrinsic uncertainties in historical storage data and assumptions regarding sectoral demand distribution and related load profiles. This minimal freedom to expand storage capacity in 2024 does not alter the overall production mix.

Throughout the simulation period, the model tends to saturate the maximum annually installable capacity for technologies such as CCGT and SCGT, highlighting the necessity to shift toward natural gas to compensate for the decommissioning of coal and oil, while simultaneously addressing demand growth and the obsolescence of the European plant fleet.

Analysing the Total Capacity of CCGT in Table 7.2, it is observed that despite the saturation of new capacity constraints, the total installed capacity decreases starting from 2035/2036; for CCGT, this decline is driven by the reduction in Residual Installed Capacity (the end-of-life of existing plants). Conversely, the analysis of SCGT Total Capacity in Table 7.2 shows that its total capacity grows and increases throughout the entire period. Furthermore, it can be underlined that SCGT reached its maximum annual production increment during the years 2028–2031 (+15% per year) and 2032 (+10% per year) and 2047–2049 (+5% per year), following a brief decline in production from 2025 to 2027 (following the maximum imposed decrease) due to the increase in CCGT production during those same years, as reported in Table 7.3.

Regarding Gas with CCS, the model saturates installable capacity starting from 2032 to facilitate the phase-out of coal and oil. Between 2025 and 2030, this technology exhibits very high Capacity Factors (CF) of approximately 0.9, as reported in Table 7.4, to cover the deficit left by fossil fuels and biomass (the latter being evaluated as non-cost-effective from a purely electrical standpoint in the absence of revenues from the thermal/cogeneration sector).

Subsequently, the CF of Gas with CCS gradually decreases, as reported in Table 7.4; the increase in the CO_2 tax and the penetration of renewables relegate it to a role of managing power peaks not covered by variable sources, although it continues to maintain relatively high CFs. Analysing the New Capacity trend for Gas with CCS in Table 7.1, it is noted that for the years 2025, 2027, and 2028, the model tends to install the power necessary to cover residual demand, choosing this technology over nuclear, biomass, or coal with CCS due to lower costs. Furthermore, the new capacity trend for Gas with CCS from 2025 to 2030, as reported in Table 7.1, is constrained by the achievement of maximum annual availability of 0.9, proving that, especially in the early years of the transition, this technology is heavily utilized to replace coal, oil, partially biomass and conventional gas, due to lower marginal cost.

The model also reduces Biomass production throughout the simulation period, as reported in Table 7.3, following the maximum imposed decrease (-5% per year), due to high operating costs and low electrical efficiency in the absence of cogeneration.

Analysing the New Capacity of nuclear power in Table 7.1, it is observed that the model tends to postpone the construction of new nuclear capacity as much as possible due to several factors: higher technological cost reductions, and there is a strategic tendency to delay investments to reduce the Total Discounted Cost and minimize the objective function. Additionally, the model prioritizes saturating and investing in more cost-effective technologies, such as gas, before building new nuclear capacity. Specifically, the model tends to saturate the maximum installable nuclear capacity between 2040 and 2050 due to cost reductions and the significant reduction in capacity that would otherwise occur from the retirement of existing plants. In 2039, the model installs only the capacity required to meet demand.

It is also observed that in this scenario, the model does not choose to invest in Coal+CCS , as evident in Table 7.1, due to high technological capex costs and the carbon tax, opting instead for more economical solutions, such as conventional gas.

Regarding Solar PV, the model tends to consistently saturate the imposed maximum capacity constraint for the years 2025–2038 and 2043–2050, as evident in Table 7.1. Between 2039 and 2042, the model installs only the capacity strictly necessary to cover residual demand, favouring this technology over others due to its lower costs.

Similarly, for Onshore Wind, the model saturates installable capacity from 2025 to 2034, as reported in Table 7.1, installing in 2035 only the capacity required to meet residual demand. From 2039, the total capacity of onshore wind begins to decline due to the reduction of residual capacity, as evident in Table 7.2. The model then ends investment in onshore wind, shifting instead to Offshore Wind, as evident in Figure 7.1, which becomes increasingly competitive due to significant assumed cost reductions and a higher assumed capacity factor.

For offshore wind, the model tends to saturate maximum installable capacity from 2034 to 2038 and from 2040 to 2050. Between 2025 and 2027, the model does not install new offshore wind capacity due to high costs and the preference for investing in CCGT and SCGT, which have high investment limits in the early years. In 2028, the model installs only enough capacity to cover residual demand, and from 2029 to 2031, it saturates the maximum available installable capacity, as evident in Figure 7.1Table 7.1, after reaching the constraint on the maximum annual production increment (+30% per year).

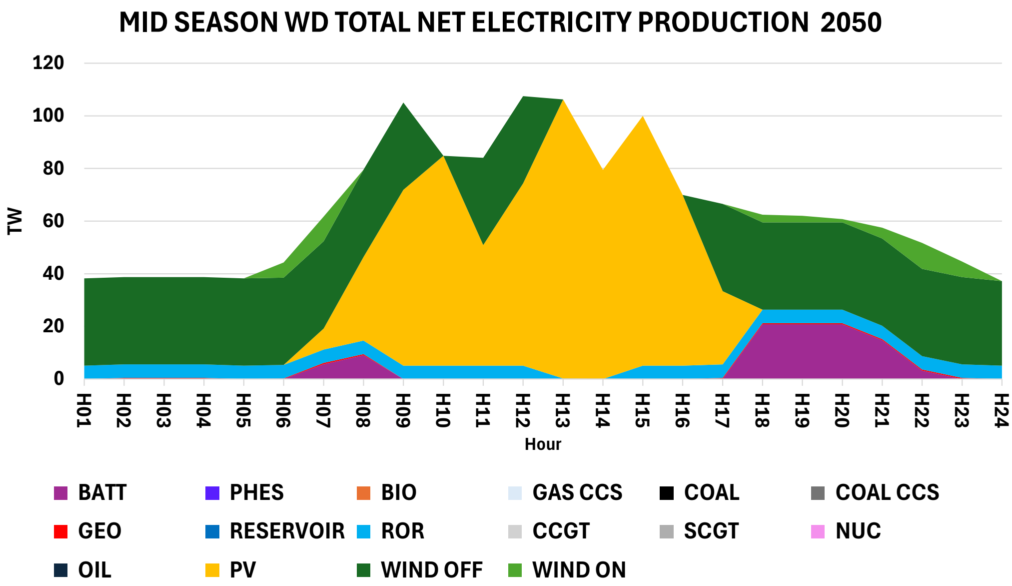

Figure 7.4: STEPS Mid-Season Workday Total Net Electricity Production 2050

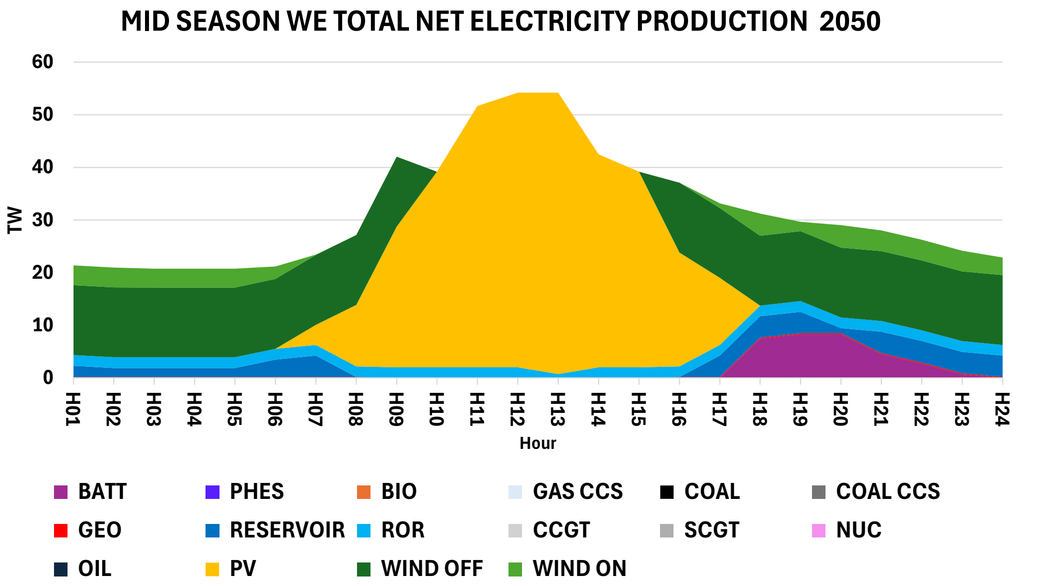

Figure 7.5: STEPS Mid-Season Weekend Total Net Electricity Production 2050

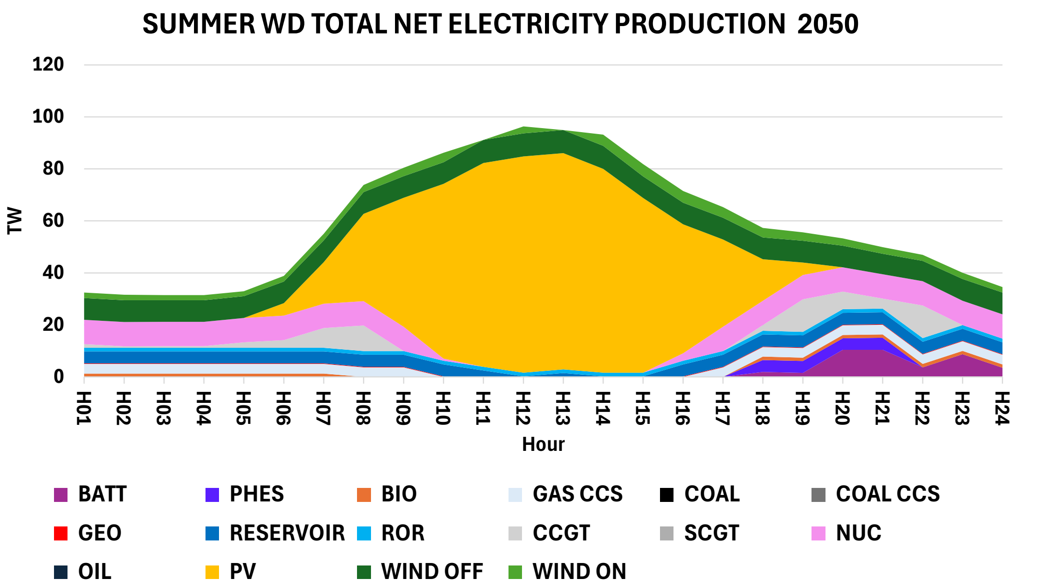

Figure 7.6: STEPS Summer Workday Total Net Electricity Production 2050

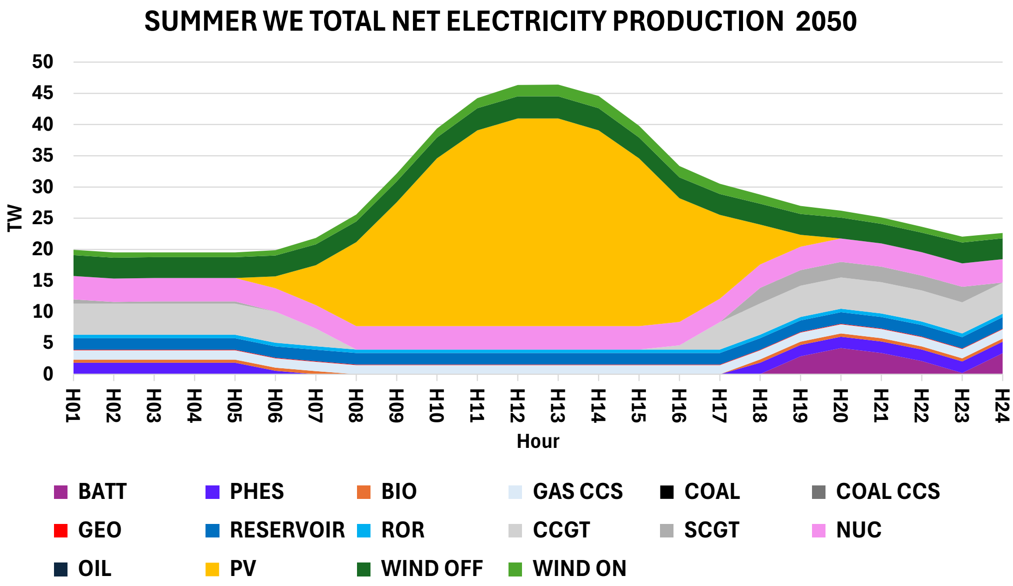

Figure 7.7: STEPS Summer Weekend Total Net Electricity Production 2050

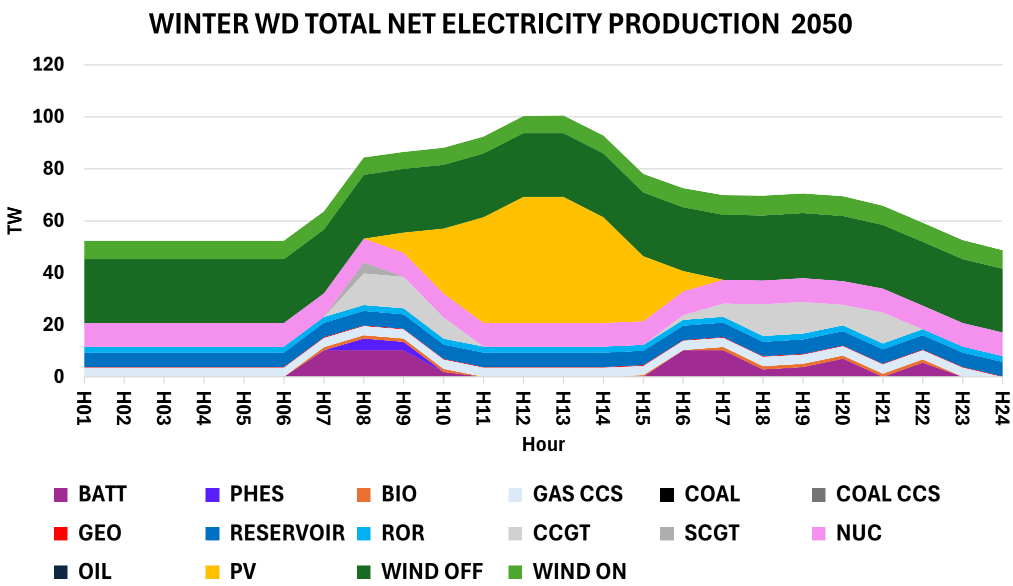

Figure 7.8: STEPS Winter Workday Total Net Electricity Production 2050

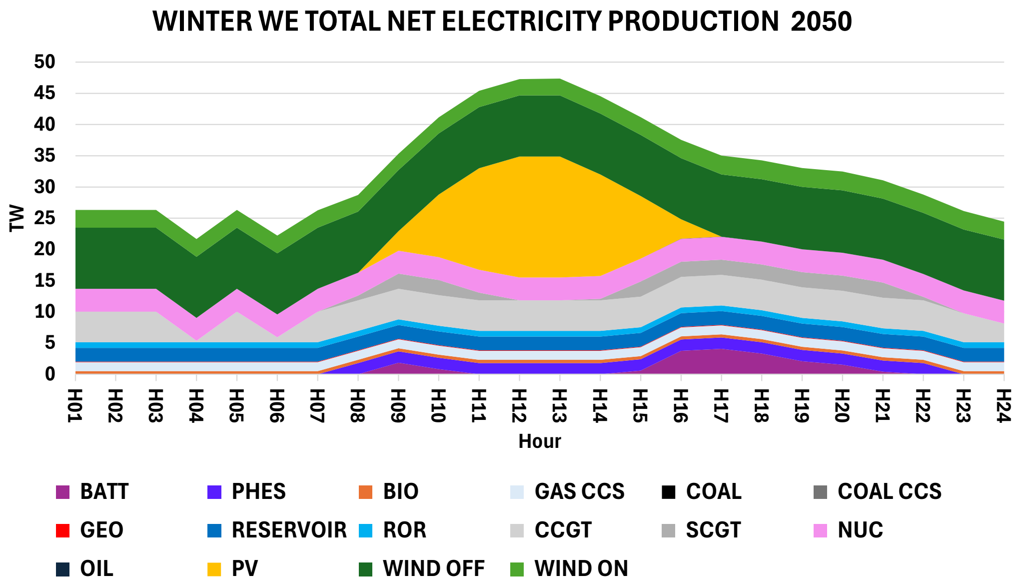

Figure 7.9: STEPS Winter Weekend Total Net Electricity Production 2050

The analysis of the 2050 production profiles across different time slices reveals highly intermittent behavior (mainly due to the lack of ramping constraints), particularly during mid-season workdays (Figure 7.4), characterized by several production peaks. It is important to underscore that these fluctuations are not driven by instantaneous demand but are a direct result of the storage charging phases. Specifically, during mid-season workdays, the model strategically schedules battery charging at hours 9, 12, 13, and 15 to enable discharging during the evening demand peak (17–22), as in Figure 7.4. During this season, the combination of high renewable availability and lower overall load allows the system to rely exclusively on renewable energy and storage. The production "valley" observed at 14 in Figure 7.4 is explained by the temporary suspension of battery charging during that specific time slice. A similar pattern is observed during mid-season weekends, where production peaks at hours 9, 11, 12, and 13 are dedicated to storage charging, as in Figure 7.5.

In the summer season workdays (Figure 7.6), the model adopts a more extended charging window: batteries are charged between 11 and 15, while Pumped Hydro Storage (PHS) is active from 9 to 17, with both discharging primarily between 17 and midnight to manage the evening cooling load. While during weekends the model charge batteries from 8 to 15 for discharging them during the evening, as in Figure 7.7.

The winter workday profile (Figure 7.8), however, exhibits a distinct dual-cycle strategy. Storage units (both batteries and PHS) are charged during the early morning hours (1–6) to mitigate the morning demand peak (7–9). A second charging cycle occurs between 11 and 14 to prepare the system for the evening peak. Winter weekends follow a similar logic, with charging phases concentrated between hours 1–3, 5, 7, and 11–13. The production spike at 5 in Figure 7.9 is explicitly linked to battery charging, ensuring availability for later discharge.

Finally, the systematic difference in production levels between workdays and weekends is primarily a function of the temporal weighting within the model. Since workdays represent 5/7 of a week compared to the 2/7 allocated to weekends, the aggregated activity and production values are proportionally higher, reflecting the greater cumulative energy demand and operational intensity of the working week.

Furthermore, analysing 2050 production by time slices, it is observed that firm and dispatchable technologies are utilized solely for managing high demand peaks, which are concentrated in winter and summer due to climatic conditions requiring higher consumption for heating and lighting in winter and air conditioning in summer. The need for peak management in 2050 in summer/winter is linked to the lower production of renewables in these seasons and the higher demand (reduced water and wind resources in summer, and reduced water and solar resources in winter).

Consequently, the model tends to underestimate batteries, preferring to manage peaks of demand with firm technologies that remain inactive during the mid-season and are activated only when renewable resources are low, leading to a reduction in their CFs. This underestimation is mainly due to intrinsic limitations in OSeMOSYS modelling and the temporal resolution adopted, which favour firm technologies over massive battery deployment:

- Capital Costs: The solver minimizes total discounted costs. Since storage CAPEX is modelled separately for power and energy and is paid entirely at the time of investment, storage is penalized compared to technologies with single CAPEX costs and variable costs paid only upon use.
- Temporal Resolution: The coarse resolution of the model intrinsically penalizes storage technologies. This is because the energy capacity of storage is defined as the product of the power component's rate of activity and the year split (duration) of the time slice. Consequently, larger time slices require significantly greater storage volumes to sustain a given power output over the entire duration of the time slice, leading to proportionally higher investment costs that often make storage less competitive compared to dispatchable.
- System Costs: To rely on batteries during peak hours, the system would require a significant surplus of renewable energy to charge them. This would necessitate over-dimensioning the renewable fleet solely to provide "charging energy," which carries its own investment cost. The optimization logic determines that the combined cost of this additional renewable

overcapacity plus the battery storage units is higher than the cost of simply installing firm, dispatchable capacity.

As a result, toward the final years of the simulation, the model prefers to install firm capacity, as evident in Table 7.1, for peaks and accept renewable curtailment rather than investing in more batteries. It is evident that the model's selection of the energy mix is fundamentally driven by least-cost optimization logic. The fact that capacity max investment constraints for both battery storage and onshore wind power remained non-binding, meaning the predefined upper limits were not reached, confirms that the model had the structural flexibility to further expand these technologies. Since OSeMOSYS did not saturate the available potential for these assets, the decision to maintain current levels is purely economic, confirming the limitations previously discussed.

However, the 2050 time slice analysis shows that PHES is correctly utilized to shift energy from periods of renewable overproduction to periods of high demand, suggesting the potential of Long-Duration Energy Storage (LDES) solutions. The fact that the model does not require onshore wind during the mid-season highlights that if other technologies, such as electrolyzers and fuel cells, had been included, the model would have had an alternative pathway to manage winter and summer peaks through seasonal storage

Finally, parallel to the production analysis, a reduction in the CF of firm technologies and an increase in curtailment (reduction in CFs for renewables) are observed in Table 7.4, a trend that will be further examined in the next scenario analysis.

CO_2 Emissions Curve Analysis

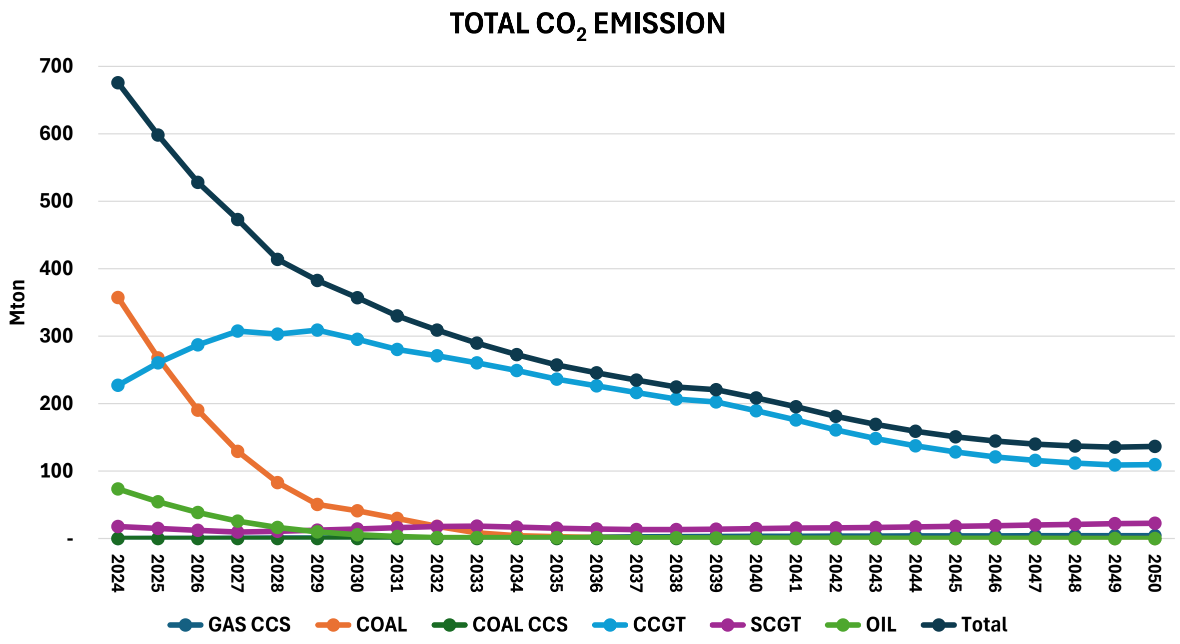

Figure 7.10: STEPS Scenario Total CO_2 Emission

The analysis of the evolution of total CO_2 emissions in the STEPS, Figure 7.10, highlights a significant decarbonization pathway, even if is less aggressive than the one observed in the APS scenario in Figure 7.20, mainly due to lower carbon tax, lower investment in renewable technologies and higher possible investment in gas technologies. The European power system exhibits a significant decrease in overall emissions, decreasing from approximately 680 Mton in 2024 to a residual value of around 140 Mton by 2050, representing a reduction of roughly 80%, as evident in Figure 7.10.

During the initial phases of the simulation, a rapid transition away from the most polluting fossil fuels is observed in Figure 7.10: emissions from coal decrease, nearly reaching zero by 2033, with a strong reduction of fuel oil as early as 2030. This drastic reduction is driven by the economic pressure of an increasing Carbon Tax, the technological obsolescence of existing coal and oil plants, and the zero Total Annual Max Capacity Investment constraint applied on these technologies. In this context, natural gas (CCGT) initially acts as a direct substitute, with its emissions peaking at approximately 300 Mton around 2029 to compensate for the gap left by coal. However, unlike more ambitious scenarios, the post-2030 decline of the CCGT capacity in the STEPS is significantly slower and more gradual, maintaining an emission contribution of about 110 Mton even in 2050. This primarily reflects the more permissive Total Annual Max Capacity Investment constraints for gas and the lower renewable penetration allowed within the scenario. The substantial presence of emissions from conventional gas plants (CCGT and SCGT) at the end of the time horizon suggests that, in the absence of more stringent regulatory constraints and policies, the solver prefers to maintain existing thermal assets in operation rather than investing in a radical technological conversion. This proves that the sole application of an increasing carbon tax and the economic driver of cost reduction for green technologies, without increased investment and/or drastic cuts to gas capacity, is insufficient to achieve zero emissions. Ultimately, the 140 Mton emission budget recorded in 2050 represents the structural limit of the STEPS scenario.

7.2. Announced Pledges Scenario (APS)

The following sections provide a detailed analysis of the primary outputs generated by the APS scenario simulation. The discussion focuses specifically on the evolution of New Capacity and Total Capacity, the dynamics of electricity Production, and the trajectory of CO_2 emissions generated by the system throughout the modelled time horizon.

New Capacity, Total Capacity and Production Analysis

Table 7.5: APS Scenario New Installed Capacity

New Capacity [GW]	BATT	PHES	BIO	GAS CCS	COAL CCS	ROR	CCGT	SCGT	NUC	PV	WIND OFF	WIND ON
2024	0.75	-	-	-	-	-	-	-	-	-	-	-
2025	1.88	3.00	-	2.00	-	0.15	6.00	2.00	0.91	91.00	-	40.00
2026	5.03	3.00	-	2.00	-	0.15	6.00	2.00	-	110.00	-	40.00
2027	1.89	3.00	-	2.00	-	-	6.00	2.00	3.00	110.00	6.17	40.00
2028	2.18	3.00	-	2.00	-	-	5.00	2.00	4.00	110.00	12.55	40.00
2029	3.50	3.00	-	2.00	-	-	5.00	2.00	4.00	110.00	16.32	40.00
2030	1.25	3.00	-	2.00	-	-	5.00	2.00	5.00	110.00	30.00	40.00
2031	1.31	2.00	-	3.00	-	-	3.00	2.00	5.00	110.00	40.00	40.00
2032	3.28	2.00	-	3.00	-	-	3.00	2.00	5.00	110.00	40.00	40.00
2033	10.96	2.00	-	3.00	-	-	3.00	2.00	5.00	110.00	50.00	6.99
2034	14.48	2.00	-	3.00	-	-	3.00	2.00	5.00	110.00	50.00	-
2035	11.25	2.00	-	5.00	-	-	3.00	2.00	7.00	110.00	50.00	-
2036	11.83	2.00	-	5.00	-	-	3.00	2.00	7.00	80.51	50.00	-
2037	12.41	2.00	-	5.00	-	-	3.00	2.00	7.00	76.44	50.00	-
2038	17.31	2.00	-	5.00	-	-	3.00	2.00	7.00	110.00	50.00	-
2039	22.68	2.00	-	5.00	-	-	3.00	2.00	7.00	83.43	50.00	-
2040	23.02	2.00	-	5.00	-	-	3.00	2.00	8.00	110.00	50.00	-
2041	27.17	2.00	-	5.00	-	-	2.00	2.00	8.00	110.00	50.00	-
2042	23.94	2.00	-	5.00	-	-	2.00	2.00	8.00	110.00	50.00	-
2043	22.94	2.00	-	5.00	1.00	-	2.00	2.00	8.00	110.00	50.00	-
2044	22.65	2.00	0.86	5.00	1.00	-	2.00	2.00	8.00	97.75	50.00	-
2045	13.63	2.00	5.00	5.00	1.00	-	2.00	2.00	10.00	80.91	50.00	-
2046	14.38	2.00	5.00	5.00	1.00	-	1.00	1.00	10.00	110.00	50.00	-
2047	14.76	2.00	5.00	5.00	1.00	-	1.00	1.00	10.00	110.00	50.00	-
2048	16.01	2.00	5.00	5.00	1.00	-	1.00	1.00	10.00	94.15	50.00	40.00
2049	17.69	2.00	5.00	5.00	1.00	-	1.00	1.00	10.00	71.39	50.00	40.00
2050	17.52	2.00	5.00	5.00	1.00	7.11	1.00	1.00	10.00	95.82	50.00	40.00

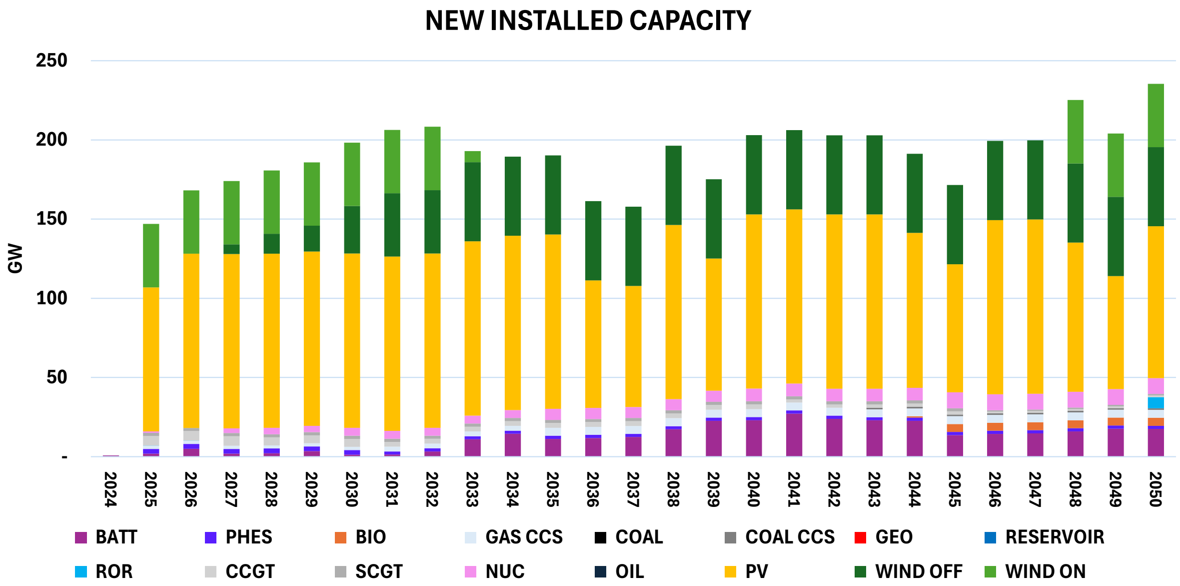

Figure 7.11: APS Scenario New Installed Capacity

Table 7.6: APS Scenario Total Installed Capacity

Total Capacity [GW]	BATT	PHES	BIO	GAS CCS	COAL	COAL CCS	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	11.85	28.90	45.11	-	152.02	-	73.20	227.93	75.98	116.10	29.50	363.97	35.67	246.19
2025	13.73	31.90	45.11	2.00	147.78	-	73.35	233.85	77.15	117.01	29.18	454.96	35.67	286.19
2026	18.76	34.90	45.11	4.00	141.63	-	73.49	239.69	78.03	117.00	28.74	564.96	35.67	326.19
2027	20.65	37.90	45.11	6.00	133.24	-	73.49	245.42	78.55	120.00	28.17	674.94	41.84	366.19
2028	22.83	40.90	45.10	8.00	122.47	-	73.49	249.94	78.65	123.98	27.43	784.91	54.39	406.19
2029	26.21	43.90	45.10	10.00	109.50	-	73.49	254.13	78.28	127.96	26.51	894.87	70.70	446.19
2030	27.42	46.90	45.08	12.00	94.81	-	73.49	257.83	77.41	132.92	25.40	1,004.79	100.70	486.19
2031	28.63	48.90	45.05	15.00	79.18	-	73.49	258.81	76.01	137.86	24.08	1,114.67	140.70	526.19
2032	31.67	50.90	45.01	18.00	63.55	-	73.49	258.81	74.11	142.74	22.56	1,224.48	180.70	566.19
2033	42.14	52.90	44.94	21.00	48.86	-	73.49	257.51	71.76	147.57	20.87	1,334.20	230.70	573.16
2034	55.76	54.90	44.83	24.00	35.89	-	73.49	254.59	69.02	152.29	19.03	1,443.77	280.70	573.13
2035	65.73	56.90	44.67	29.00	25.13	-	73.49	249.77	66.02	158.87	17.09	1,553.13	330.70	573.04
2036	75.95	58.90	44.43	34.00	16.73	-	73.49	242.83	62.87	165.26	15.09	1,632.74	380.70	572.85
2037	86.62	60.90	44.09	39.00	10.58	-	73.49	233.70	59.73	171.37	13.10	1,707.87	430.70	572.45
2038	102.32	62.90	43.61	44.00	6.34	-	73.49	222.47	56.72	177.14	11.15	1,816.08	480.70	571.65
2039	122.98	64.90	42.96	49.00	3.60	-	73.49	209.44	53.99	182.46	9.31	1,897.09	530.70	570.17
2040	143.26	66.90	42.10	54.00	1.94	-	73.49	195.07	51.63	188.26	7.62	2,003.85	580.70	567.58
2041	164.91	68.90	41.00	59.00	0.98	-	73.49	179.00	49.73	193.42	6.11	2,109.63	630.70	563.32
2042	186.71	70.90	39.63	64.00	0.47	-	73.49	162.93	48.33	197.89	4.79	2,214.24	680.70	556.74
2043	207.37	72.90	37.96	69.00	0.21	1.00	73.49	147.56	47.46	201.59	3.67	2,317.50	730.68	547.17
2044	226.49	74.90	36.85	74.00	0.09	2.00	73.49	133.53	47.09	204.52	2.75	2,406.98	780.65	534.12
2045	238.86	76.90	39.58	79.00	0.04	3.00	73.49	121.30	47.19	208.70	2.02	2,477.96	830.56	517.39
2046	251.93	78.90	42.06	84.00	0.01	4.00	73.49	110.17	46.72	212.19	1.44	2,576.27	880.35	497.22
2047	263.41	80.90	44.31	89.00	0.01	5.00	73.49	101.24	46.59	215.12	1.01	2,672.79	929.89	474.39
2048	268.45	82.90	46.40	94.00	-	6.00	73.49	94.41	46.77	217.64	0.69	2,751.71	979.00	490.09
2049	271.66	84.90	48.42	99.00	-	7.00	73.49	89.49	47.18	219.96	0.46	2,806.24	1,027.45	505.79
2050	277.94	86.90	50.43	104.00	-	8.00	80.60	86.19	45.76	222.28	0.30	2,883.77	1,075.04	482.95

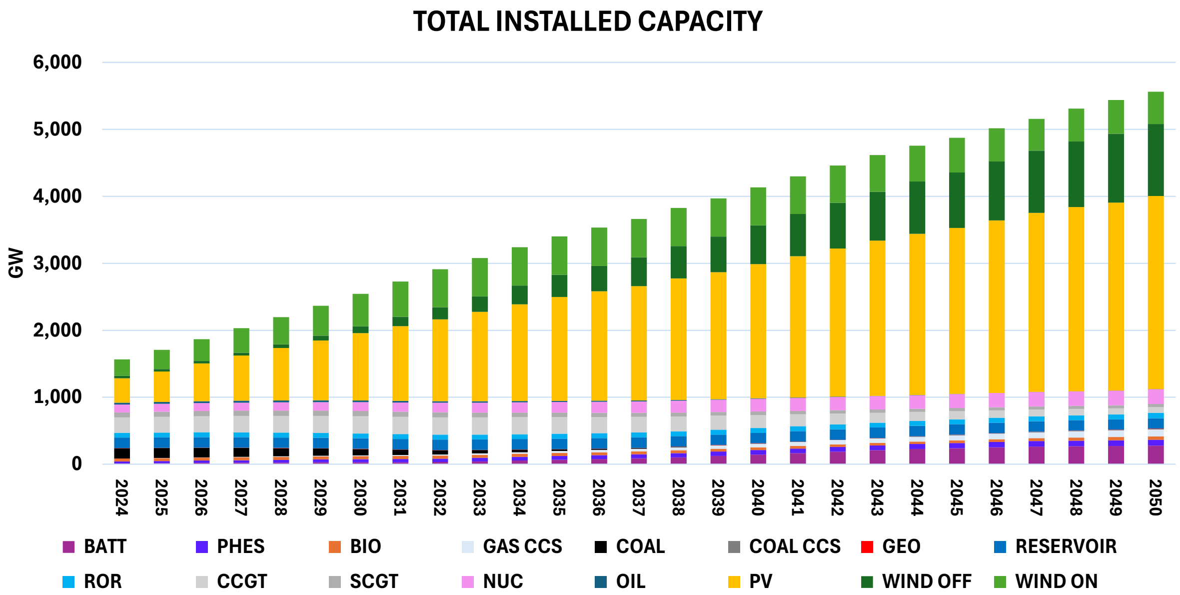

Figure 7.12: APS Scenario Total Installed Capacity

Table 7.7: APS Scenario Total Net Electricity Production

Production [TWh]	BATT	PHES	BIO	GAS CCS	COAL	COAL CCS	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	2.5	2.2	191.9	-	434.0	-	24.2	374.0	293.2	654.4	34.4	742.0	102.4	384.9	99.9	519.2
2025	0.6	2.4	182.3	15.8	325.5	-	24.2	374.0	293.7	719.8	29.3	768.8	76.8	481.1	99.9	603.5
2026	6.4	9.5	173.2	31.5	231.1	-	24.2	374.0	294.3	750.9	24.0	807.2	54.5	597.4	99.9	687.8
2027	7.6	23.7	164.5	47.3	157.2	-	24.2	374.0	294.3	749.6	18.7	841.0	37.1	713.7	117.2	767.9
2028	29.5	57.0	156.3	56.6	100.6	-	24.2	374.0	294.3	704.7	15.4	908.2	23.7	830.0	152.3	832.0
2029	34.3	85.1	148.5	41.9	61.4	-	24.2	374.0	294.3	726.1	16.9	894.7	14.5	946.3	198.0	893.5
2030	28.5	94.5	141.1	48.5	49.7	-	24.2	374.0	294.2	692.0	18.6	846.7	8.3	1,062.6	257.4	971.6
2031	29.1	103.2	134.0	60.6	35.8	-	24.2	374.0	293.6	640.8	20.5	797.2	4.5	1,178.8	347.6	1,032.5
2032	32.9	108.5	127.3	72.5	23.9	-	24.2	374.0	293.0	585.0	22.5	750.6	2.5	1,291.2	469.2	1,063.4
2033	51.0	110.4	120.9	82.1	14.2	-	24.1	374.0	292.4	543.0	24.8	717.3	2.8	1,377.2	626.9	1,054.3
2034	78.6	115.1	114.9	93.8	6.1	-	24.1	374.0	291.9	506.4	26.5	685.4	2.7	1,490.0	751.5	1,044.1
2035	108.7	121.7	109.2	109.9	4.4	-	24.0	374.0	291.3	459.5	22.7	664.4	2.6	1,576.5	893.1	1,037.7
2036	135.6	121.7	103.7	126.3	3.0	-	24.0	373.3	290.7	421.0	20.4	663.4	2.4	1,639.1	1,013.5	1,044.4
2037	157.5	107.5	98.5	142.1	1.9	-	23.9	372.5	290.1	384.2	18.8	685.5	2.2	1,720.0	1,155.9	980.2
2038	180.6	91.1	93.6	157.2	1.1	-	23.9	371.8	289.5	339.2	17.6	704.3	2.0	1,763.0	1,290.7	972.2
2039	207.1	78.1	88.9	173.9	0.6	-	23.8	371.0	289.0	302.2	17.1	723.6	1.7	1,833.1	1,395.1	957.9
2040	234.7	74.5	84.5	190.3	0.4	-	23.8	370.3	288.4	257.0	16.8	743.5	1.5	1,923.3	1,529.9	903.0
2041	260.8	76.3	80.2	208.5	0.2	-	23.7	369.6	287.8	212.6	17.2	761.1	1.3	1,997.1	1,631.6	897.7
2042	285.6	85.2	76.2	227.1	0.1	-	23.7	368.8	287.2	171.5	18.5	776.3	1.0	2,084.0	1,733.6	878.9
2043	308.4	93.6	72.4	246.2	0.1	-	23.6	368.1	286.7	130.7	20.3	788.7	1.2	2,096.5	1,956.0	810.5
2044	321.0	87.3	68.8	252.1	0.1	7.7	23.6	367.3	286.1	108.2	22.4	798.9	0.5	2,230.9	2,003.6	786.7
2045	372.5	84.2	65.4	254.5	0.0	11.5	23.5	366.6	285.5	96.8	23.7	815.0	0.4	2,359.9	2,107.9	703.8
2046	336.7	85.8	62.1	253.6	0.0	15.4	23.5	365.9	284.9	87.4	24.2	828.1	0.3	2,296.1	2,280.0	742.1
2047	323.4	87.4	59.0	256.4	0.0	19.2	23.5	365.1	284.4	80.1	24.7	839.0	0.2	2,412.9	2,335.0	715.1
2048	350.2	87.9	56.0	238.7	-	23.1	23.4	364.4	284.9	71.5	21.2	845.7	0.1	2,568.0	2,406.5	667.2
2049	323.5	85.4	53.2	227.1	-	26.9	23.4	363.7	285.5	66.9	18.4	854.0	0.1	2,441.1	2,631.3	728.2
2050	434.4	88.5	50.6	230.5	-	30.8	23.3	363.0	286.1	63.8	17.1	862.5	0.1	2,685.2	2,735.6	537.4

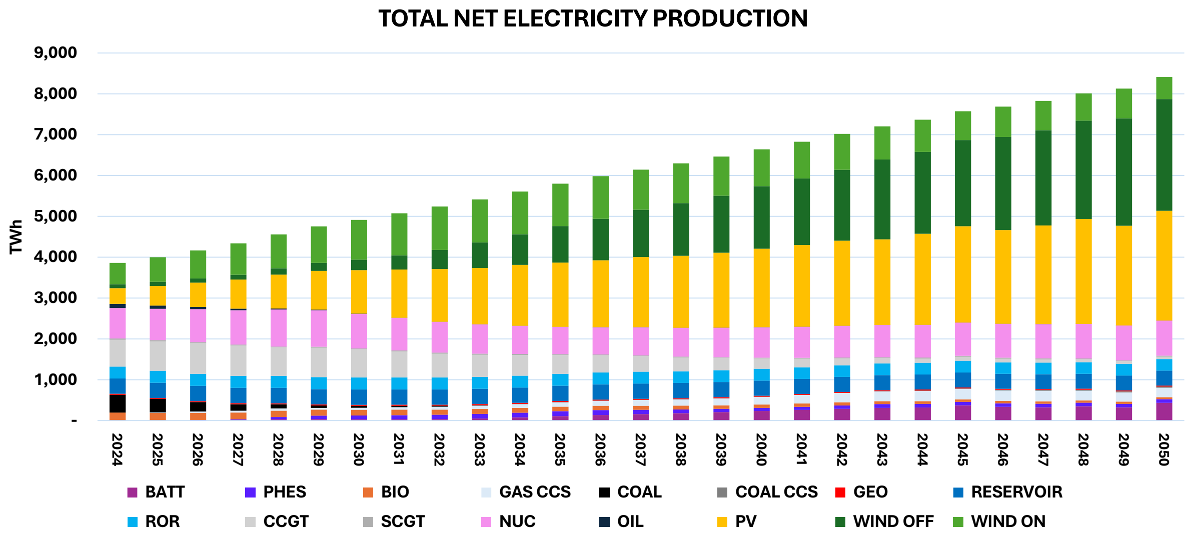

Figure 7.13: APS Scenario Total Net Electricity Production

Table 7.8: APS Scenario Capacity Factor

Capacity factor	BIO	GAS CCS	COAL	COAL CCS	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	0.49	-	0.33	-	0.81	0.27	0.46	0.33	0.05	0.73	0.40	0.12	0.32	0.24
2025	0.46	0.90	0.25	-	0.81	0.27	0.46	0.35	0.04	0.75	0.30	0.12	0.32	0.24
2026	0.44	0.90	0.19	-	0.81	0.27	0.46	0.36	0.04	0.79	0.22	0.12	0.32	0.24
2027	0.42	0.90	0.13	-	0.81	0.27	0.46	0.35	0.03	0.80	0.15	0.12	0.32	0.24
2028	0.40	0.81	0.09	-	0.81	0.27	0.46	0.32	0.02	0.84	0.10	0.12	0.32	0.23
2029	0.38	0.48	0.06	-	0.81	0.27	0.46	0.33	0.02	0.80	0.06	0.12	0.32	0.23
2030	0.36	0.46	0.06	-	0.81	0.27	0.46	0.31	0.03	0.73	0.04	0.12	0.29	0.23
2031	0.34	0.46	0.05	-	0.81	0.27	0.46	0.28	0.03	0.66	0.02	0.12	0.28	0.22
2032	0.32	0.46	0.04	-	0.81	0.27	0.46	0.26	0.03	0.60	0.01	0.12	0.30	0.21
2033	0.31	0.45	0.03	-	0.81	0.27	0.45	0.24	0.04	0.55	0.02	0.12	0.31	0.21
2034	0.29	0.45	0.02	-	0.81	0.27	0.45	0.23	0.04	0.51	0.02	0.12	0.31	0.21
2035	0.28	0.43	0.02	-	0.81	0.27	0.45	0.21	0.04	0.48	0.02	0.12	0.31	0.21
2036	0.27	0.42	0.02	-	0.80	0.27	0.45	0.20	0.04	0.46	0.02	0.11	0.30	0.21
2037	0.26	0.42	0.02	-	0.80	0.27	0.45	0.19	0.04	0.46	0.02	0.11	0.31	0.20
2038	0.24	0.41	0.02	-	0.80	0.27	0.45	0.17	0.04	0.45	0.02	0.11	0.31	0.19
2039	0.24	0.41	0.02	-	0.80	0.27	0.45	0.16	0.04	0.45	0.02	0.11	0.30	0.19
2040	0.23	0.40	0.02	-	0.80	0.27	0.45	0.15	0.04	0.45	0.02	0.11	0.30	0.18
2041	0.22	0.40	0.02	-	0.80	0.27	0.45	0.14	0.04	0.45	0.02	0.11	0.30	0.18
2042	0.22	0.41	0.02	-	0.80	0.27	0.45	0.12	0.04	0.45	0.02	0.11	0.29	0.18
2043	0.22	0.41	0.04	-	0.79	0.27	0.45	0.10	0.05	0.45	0.04	0.10	0.31	0.17
2044	0.21	0.39	0.08	0.44	0.79	0.27	0.44	0.09	0.05	0.45	0.02	0.11	0.29	0.17
2045	0.19	0.37	0.05	0.44	0.79	0.27	0.44	0.09	0.06	0.45	0.02	0.11	0.29	0.16
2046	0.17	0.34	0.02	0.44	0.79	0.27	0.44	0.09	0.06	0.45	0.02	0.10	0.30	0.17
2047	0.15	0.33	0.02	0.44	0.79	0.27	0.44	0.09	0.06	0.45	0.02	0.10	0.29	0.17
2048	0.14	0.29	-	0.44	0.79	0.27	0.44	0.09	0.05	0.44	0.02	0.11	0.28	0.16
2049	0.13	0.26	-	0.44	0.78	0.27	0.44	0.09	0.04	0.44	0.02	0.10	0.29	0.16
2050	0.11	0.25	-	0.44	0.78	0.27	0.41	0.08	0.04	0.44	0.02	0.11	0.29	0.13

From the analysis of the output related to New Capacity in the APS scenario in Table 7.5, it emerges that the model does not invest in new technologies for Coal, Oil, Geothermal (Geo), and large hydroelectric reservoirs (Reservoir). This is consistent with the imposed zero Total Annual Max Capacity Investment constraint, which reflects two main motivations: the assumed policy phase-out of coal and more carbon-intensive technologies like oil, and the limited availability in Europe of new suitable sites for conventional geothermal and new hydroelectric reservoir.

In the simulation's starting year (2024), the model installed approximately 0.75 GW of batteries, as evident in Table 7.5. This is permitted by a specific model setting: a zero Total Annual Max Capacity Investment constraint was imposed on all production technologies for the year 2024, with the objective of forcing the system to maintain an installed capacity configuration exactly linked to the calibrated RES benchmark. The only exception was deliberately reserved for electrochemical battery storage, to provide the solver with a technical flexibility to respect balance constraints and satisfy electricity demand, reducing the impact of intrinsic uncertainties in historical storage data and assumptions regarding sectoral demand distribution and related load profiles. However, this minimal freedom of storage capacity expansion in 2024 does not modify the overall production mix.

Analyzing the New Capacity output in Table 7.5 is evident that the model tends to saturate the maximum annually installable capacity for technologies such as Gas CCS, CCGT, and SCGT for the entire simulation period, highlighting the need to move toward natural gas to compensate for the decommissioning of coal and oil, while simultaneously meeting rising electricity demand and addressing the obsolescence of the aging European power plant fleet.

Analyzing the Total Capacity of CCGT and SCGT in Table 7.6, it is observed that, despite the saturation of new capacity constraints, the total installed capacity decreases starting from 2031/2032 for CCGT and from 2030 for SCGT. This decline is driven by the reduction of the Residual Installed Capacity due to the end-of-life of the existing plants.

Regarding Gas with CCS, the model saturates the max installable capacity per year, favoring the phase-out of coal and oil, as evident in Table 7.6. Between 2025 and 2028, this technology is characterized by very high-Capacity Factors (CF ≈ 0.9) to cover the reduction of electricity production of coal, oil and biomass (the latter evaluated as non-convenient from a purely electrical point of view in the absence of revenue from the thermal/cogeneration sector), as evident in Table 7.8.

Subsequently, the CF of Gas CCS gradually decreases; the increase in the CO_2 tax and the penetration of renewables relegate it to a role of managing power peaks not covered by variable sources.

The model also reduces production from Biomass throughout the simulation period following the maximum imposed decrement (-5% per year), as evident in Table 7.7. It is important to note that the model penalizes biomass due to the exclusion of the thermal and heating sectors from the system boundaries. Under the current framework, the technology is characterized by high operational costs and low electrical-only efficiency. However, biomass competitiveness is significantly increased by revenues from cogeneration (heat production), as well as by state subsidies and green certificates. The absence of these economic drivers and thermal revenues in the model leads to a more pronounced reduction in biomass activity than what might be observed in a real-world, policy-supported environment.

However, in the last five years of the time horizon, a new installation of biomass is observed in Table 7.5 (saturating the annual installable maximum) with reduced CFs (Table 7.8), confirming its use for peak management.

Analyzing coal production in Table 7.7 throughout the simulation period, it is observed that it follows the maximum imposed decrement. This highlights how the combination of an increasing carbon tax and the end-of-life retirement of coal plants drives the model toward a rapid reduction in coal-fired power generation.

From 2043, the model also invests in Coal with CCS, saturating the maximum annual installable limit allowed, as evident in Table 7.5. This technology operates with a CF of approximately 0.44, being employed exclusively to manage demand peaks and compensate for the massive decommissioning of CCGT, SCGT, and biomass at the end of their life. The model's decision to invest in Coal with CCS, despite the rising carbon tax, is necessitated by the saturation of other technology options.

Regarding Nuclear, however, the model saturates the installable capacity from 2027 (Table 7.5), driven by the reduction of CAPEX and the retirement of the existing fleet. For the years 2025 and 2026, the maximum installable capacity is limited by reaching the annual increment limits in 2026 (+5% per year) and the maximum availability imposed in 2025 (0.75).

Regarding Wind Offshore, from 2030, the model constantly saturates the maximum installation capacity thanks to the reduction in costs and higher CFs compared to onshore, making it a dominant technology, as evident in Table 7.5. After an initial lack of investments (2025-2026) due to the high costs of the technology, the model invested in 2027 to cover exactly the residual electricity demand. For the years from 2028 to 2030, the maximum available installable capacity is limited by the constraint on the maximum percentage increase in electricity production reached (+30% per year).

Wind Onshore, on the other hand, shows a much more discontinuous New Capacity trend, as evident in Table 7.5 and Figure 7.11. It saturates the max capacity investment constraint until 2032, in 2033 it installs only what is needed to cover unmet demand and then stops and resumes only from 2048 to replace end-of-life plants and cover peak demand. In fact, for wind onshore, the total capacity is characterized by a marked drop starting from 2040 due to the retirement of older plants, as evident in Table 7.6. This discontinuous behavior is typical of discounted cost minimization, in which the solver postpones investments to reduce the impact on the objective function and increase the salvage value, rather than anticipating investments and favoring more gradual and less discontinuous solutions.

Solar PV instead presents a more gradual New Capacity growth, as evident in Table 7.5. The model saturates the maximum capacity for several periods such as 2026-2035, 2038, 2040-2043, and 2046-2047. For the years 2025 and 2050, it installs the maximum allowed capacity due to reaching the maximum production percentage increase (+25% and +10% per year respectively). For the years 2036, 2037, 2039, 2044, 2045, 2048, and 2049, the model instead installs only what is needed to cover residual demand.

Finally, the model installs 7 GW of run-of-river in 2050, as evident in Table 7.5, saturating the maximum capacity of the technology only in 2050, when electricity demand is at its maximum and residual firm capacity is at its minimum. Here, too, the postponement of investment is a strategy for optimizing the salvage value and reducing discounted cost.

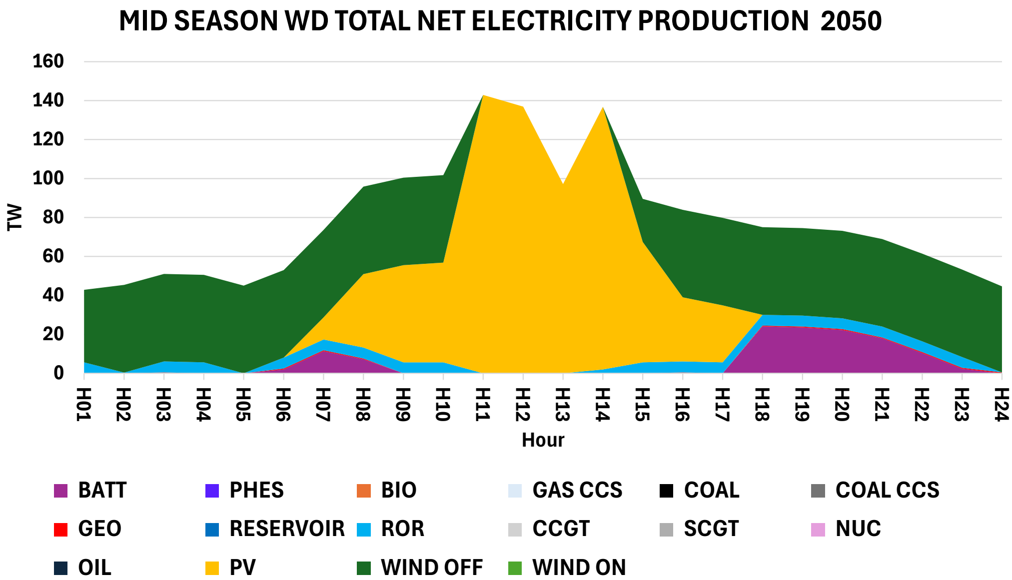

Figure 7.14: APS Mid-Season Workday Total Net Electricity Production 2050

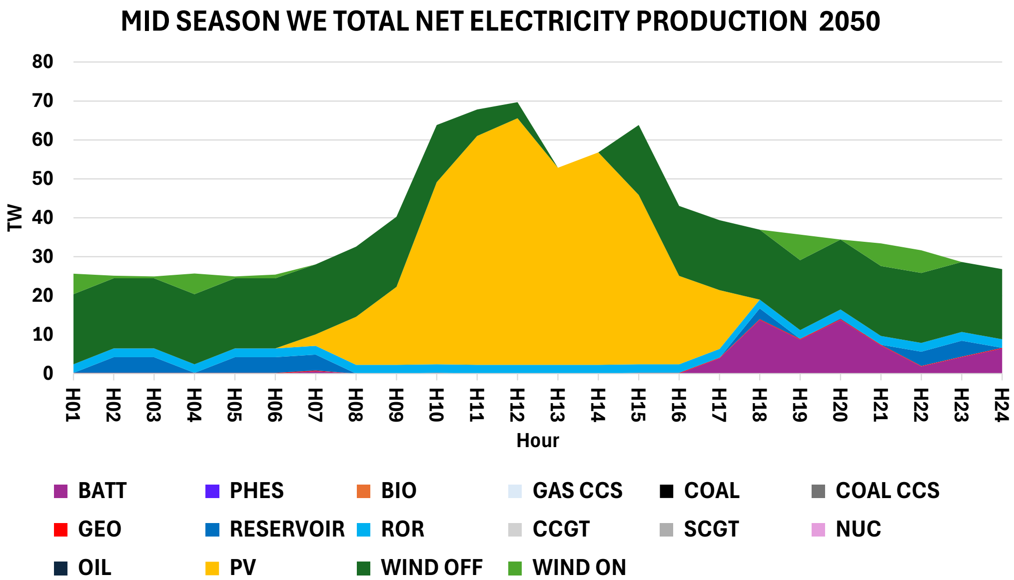

Figure 7.15: APS Mid-Season Weekend Total Net Electricity Production 2050

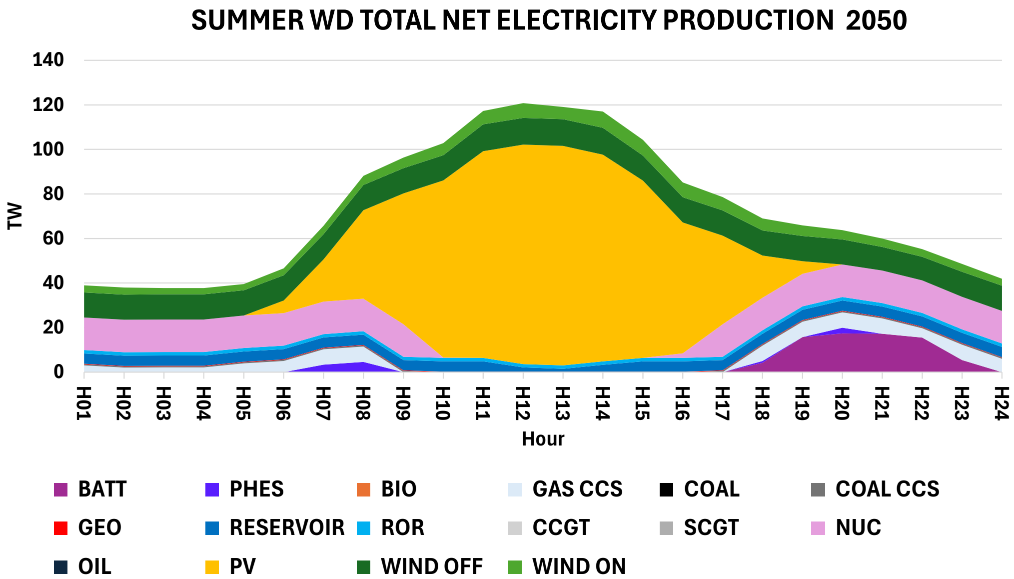

Figure 7.16: APS Summer Workday Total Net Electricity Production 2050

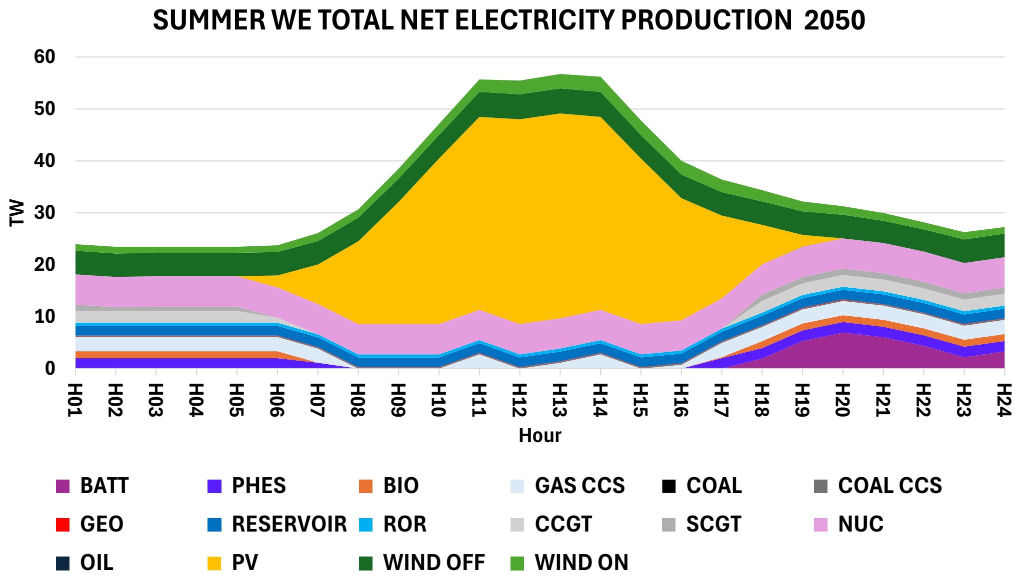

Figure 7.17: APS Summer Weekend Total Net Electricity Production 2050

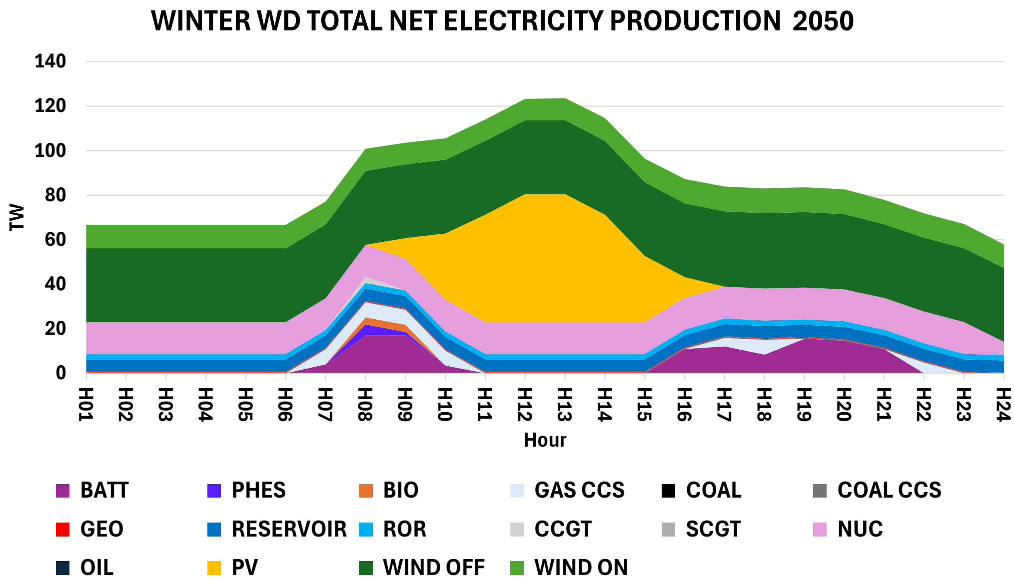

Figure 7.18: APS Winter Workday Total Net Electricity Production 2050

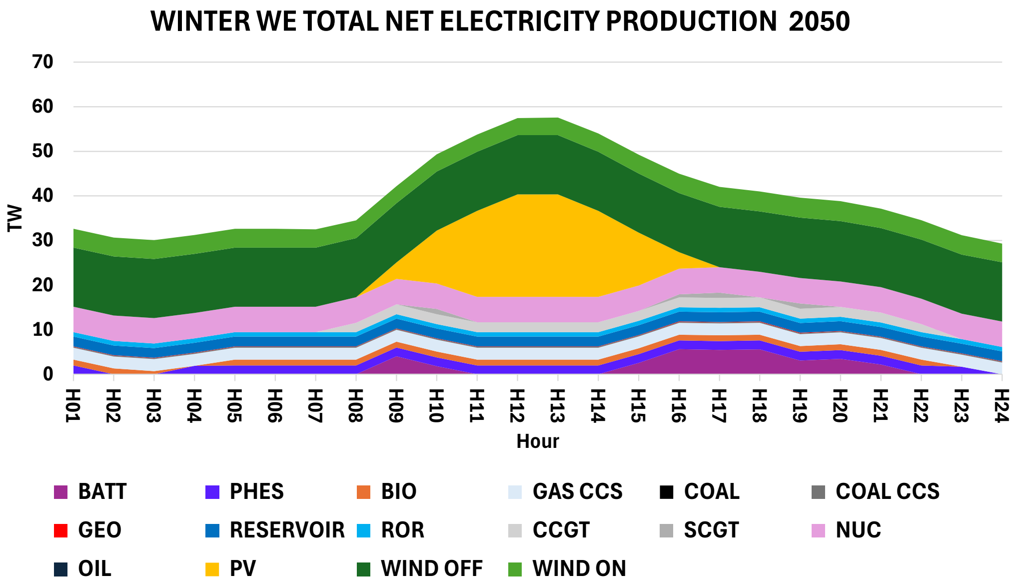

Figure 7.19: APS Winter Weekend Total Net Electricity Production 2050

The analysis of the 2050 production profiles across different time slices reveals a highly intermittent behavior (mainly due to the lack of ramping constraints), particularly during mid-season workdays (Figure 7.14) characterized by several production peaks. It is important to underscore that these fluctuations are not driven by instantaneous demand but are a direct result of the storage charging phases. Specifically, during mid-season workdays, the model strategically schedules battery charging at hours 3, 4, 11, 12, 14 to enable discharging during the morning peak (7-8) and evening demand peak (17–23), as in Figure 7.14. During this season, the combination of high renewable availability and lower overall load allows the system to rely exclusively on renewable energy and storage. The production 'valley' observed at 13 in Figure 7.14 is explained by the temporary suspension of battery charging during that specific time slice. A similar pattern is observed during mid-season weekends, where production peaks at hours 10, 11, 12, 14, 15 (Figure 7.15) are dedicated to storage charging. Moreover, the production 'valley' observed also in this case at 13 in Figure 7.15 is due to the temporary suspension of the charging phase.

In the summer season, batteries are charged between 11 and 15, while Pumped Hydro Storage (PHS) from 9 to 17, with both discharging primarily between 17 and midnight to manage the evening cooling load, as in Figure 7.16. During the summer weekend the model charges batteries from 8-15, for then discharging them for the evening peak, as in Figure 7.17.

In the winter workday profile in Figure 7.18, storage units (both batteries and PHS) are charged during the early morning hours (1-6) to mitigate the morning demand peak (7–9). A second charging cycle occurs between 11 and 13, and then from 14 to

15 the model charge batteries to prepare the system for the evening peak. Winter weekends follow a similar logic, with charging phases concentrated between hours 1-7, and 12–14, as in Figure 7.19.

Finally, the systematic difference in production levels between workdays and weekends is primarily a function of the temporal weighting within the model.

The analysis of production in 2050, divided by time slices, confirms the model's tendency to install firm technologies to cover only demand peaks in winter and summer:

- Biomass: Used in summer time slices during weekends (Figure 7.17), night hours (1-6), and evening hours (18-24), when renewables are scarce and demand is increased by residential air conditioning, as well as during winter peaks (hours 8-9 of working days and weekends) to compensate for low production from solar and run-of-river hydroelectricity, as in Figure 7.18 and Figure 7.19.
- Gas CCS and Coal CCS: Follow similar trends, with increased use on winter weekends and during morning and evening peaks in summer and winter, especially during the hottest hours of the day given the high use of residential air conditioning, as evident in Figure 7.16, Figure 7.17, Figure 7.18, Figure 7.19.
- CCGT and SCGT: Employed to cover residual night and evening demand in summer and winter weekend loads, as evident in Figure 7.16, Figure 7.17, Figure 7.18, Figure 7.19.
- Nuclear: Maintains, on the contrary, a regular and constant production profile limited to winter and summer time slices, as evident in Figure 7.16, Figure 7.17, Figure 7.18, Figure 7.19.

A fundamental aspect emerges in Midseason: technologies such as CCS (gas/coal), CCGT, SCGT, and nuclear remain inactive as evident in Figure 7.14 and Figure 7.15

During the mid-season, electricity demand is lower due to the mild climate that reduces the requirement for space heating and cooling. Simultaneously, environmental conditions are exceptionally favourable for renewable generation: wind production remains high, photovoltaic systems achieve high performances, and hydrological availability is at its peak, as water resources are favoured by the seasonal melting of winter snow and ice in the mountainous regions, providing an abundant supply that is not yet impacted by the risk of summer droughts. This reflects the assumed distribution of renewable CFs across different time slices and the profile of electricity demand in this season. In this season, the model manages demand exclusively with renewables and batteries, as evident in Figure 7.14 and Figure 7.15.

In contrast, the system faces significant challenges during summer and winter due to extreme demand peaks. In winter, high consumption for heating coincides with limited solar and water resources. In summer, increased air conditioning demand aligns with lower wind and water availability. To cover these seasonal gaps, the model installs dispatchable firm capacity; however, these assets remain underutilized (low Capacity Factors) for most of the year due to their higher operating costs, as evident in Table 7.8.

Furthermore, another fundamental aspect to observe is that PHES (Pumped Hydro Energy Storage) is correctly used by the model to shift energy from time slices where demand is low and renewable production is abundant, to winter and summer peak time slices. However, the use of PHES is limited by the constraint on maximum annual installable capacity, which reflects the installation limits of the technology.

Batteries, on the other hand, are used for daily peak management. It is observed how they discharge the excess energy produced during hours of high renewable production into moments of peak demand, predominantly in the evening.

The model tends to underestimate batteries, preferring to manage winter/summer seasonal peaks with firm technologies, as already discussed in the previous scenario. This is due to intrinsic limits of the OSeMOSYS modeling and the adopted temporal resolution:

- Capital Costs: The solver minimizes total discounted costs. Since the CAPEX cost of storage is modeled separately for the power part and the storage part, and is paid entirely upon investment, storage is penalized compared to technologies with single CAPEX costs and variable costs paid only upon use.
- Temporal Resolution: The coarse resolution of the model intrinsically penalizes storage technologies. This is because the energy capacity of storage is defined as the product of the power component's rate of activity and the year split (duration) of the time slice. Consequently, larger time slices require significantly greater storage volumes to sustain a given power output over the entire duration of the time slice, leading to proportionally higher investment costs that often make storage less competitive compared to dispatchable technologies.
- System Costs: To rely on batteries during peak hours, the system would require a significant surplus of renewable energy to charge them. This would necessitate over-dimensioning the renewable fleet solely to provide "charging energy," which carries its own investment cost. The optimization logic determines that the combined cost of this additional renewable

overcapacity plus the battery storage units is higher than the cost of simply installing firm, dispatchable capacity (such as gas or biomass).

Consequently, toward the final years of the simulation (characterized by a more marked retirement of firm technologies due to end-of-life), the model still prefers to install firm capacity to be used only for peaks and to perform curtailment of renewables, rather than installing batteries, given the intrinsically higher costs, as discussed also in the previous scenario.

A possible solution could be the integration of Long-Duration Energy Storage (LDES) such as green hydrogen, produced by an electrolyzer during hours of renewable surplus, stored, and then converted back into electricity by a fuel cell to cover demand peaks. The fact that the model does not require onshore wind during the mid-season 2050 highlights that if other technologies, such as electrolyzers and fuel cells, had been included, the model would have had an alternative pathway to manage winter and summer peaks through seasonal storage.

Capacity Factor (CF) reduction and Curtailment

Toward the end of the time horizon, two linked phenomena are observed: the reduction of the Capacity Factors (CF) of conventional technologies and the simultaneous increase in the curtailment of Variable Renewable Energy (VRE) sources (reduction of their CFs), as evident in Table 7.8.

The reduction in CF for biomass, nuclear, CCGT, SCGT, and CCS-equipped technologies (Table 7.8) is due to the Merit Order logic applied to residual demand: sources with zero marginal cost (solar PV and Wind), characterized by dispatch priority, relegating thermal plants to the role of Firm Capacity for managing peaks of demand.

This decline is further favored by two methodological limitations:

- Absence of Ramping Constraints: Without physical limits on the rate of power variation for these plants, the solver can instantaneously activate and deactivate conventional units to cover only peaks of residual demand. This occurs without the need to maintain them at a "technically minimum" operating level, which would necessarily result in higher CFs.
- Absence of Start-up, Shut-down, and Ramping Costs: The model eliminates the economic penalties associated with starting, stopping, or varying the load of thermal units, such as extra fuel consumption or mechanical wear. Without these financial costs, the solver treats programmable assets as perfectly flexible tools, utilizing them only for short-term peak-shaving operations. In a real-world market, the costs linked to cycling cycles would instead incentivize a more constant and stable production profile.

Parallel to this, a progressive increase in curtailment (that is the reduction of the measured capacity factor from the theoretical value for renewables), referring to the forced reduction of excess renewable production, is observed toward the final years of the simulation, as in Table 7.8. This phenomenon arises from the necessary oversizing of VRE capacity to ensure demand coverage during periods of low natural resource availability.

In this context, two additional structural limitations favored this phenomenon:

- "Copper Plate" Assumption (Single Macro-Region): The absence of interconnections with external systems and regions prevents the model from exporting energy surpluses to neighboring areas. Consequently, excess energy must be absorbed locally or curtailed, artificially increasing curtailment levels.
- Storage Inefficiency: Due to the low temporal resolution, the energy investment required to store surpluses is economically prohibitive compared to the zero marginal cost of the wasted resource.

In summary, the model identifies curtailment and the low utilization of programmable capacity as an economically optimal solution. In a decarbonized and isolated system, it is more rational to accept technical inefficiency (waste of renewable energy and underutilized thermal assets) than to sustain the extremely high capital costs required for storage.

Linear Trend of Total Capacity and Electricity Production

There is a fundamental parallelism between the evolution of electricity demand and the structural response of the system: total installed capacity (Figure 7.12) has a linear trend that follows the linear demand trajectory evolution assumed. Although individual technologies may show discontinuous dynamics, aggregate capacity grows regularly and linearly due to the Energy Balance Constraints.

The model is constrained to satisfy electricity demand in every single Time Slice. Since total demand and peak loads grow linearly, the solver is forced to expand total capacity to meet demand, following the same growth trend. The perfect symmetry between the linear growth of demand and that of total installed capacity demonstrates that the system expands at the same rate as demand growth to minimize overall costs. Furthermore, the total production profile (Figure 7.13) also follows a linear trend, dictated also in this case by the demand satisfaction constraint and the linear nature of the demand growth itself.

Discrepancy between Installed Capacity and Production

Finally, a contrast is observed between the volumes of capacity (Figure 7.12) and electricity generation (Figure 7.13). Although renewables dominate the installed power mix, their contribution in terms of energy produced appears to be proportionally reduced due to three main factors:

- The Impact of Capacity Factors: Unlike thermal plants, renewables are limited by the natural availability of the resource.
- The Role of Curtailment: As previously analyzed, the loss of surplus energy reduces the net energy contribution of VREs.
- Oversizing Renewables for Peak Coverage: Since demand peaks often do not coincide with moments of maximum renewable production, the model must oversize the installed capacity to ensure that, even in low-production conditions, there is sufficient instantaneous power to cover the load.

CO_2 Emissions Curve Analysis

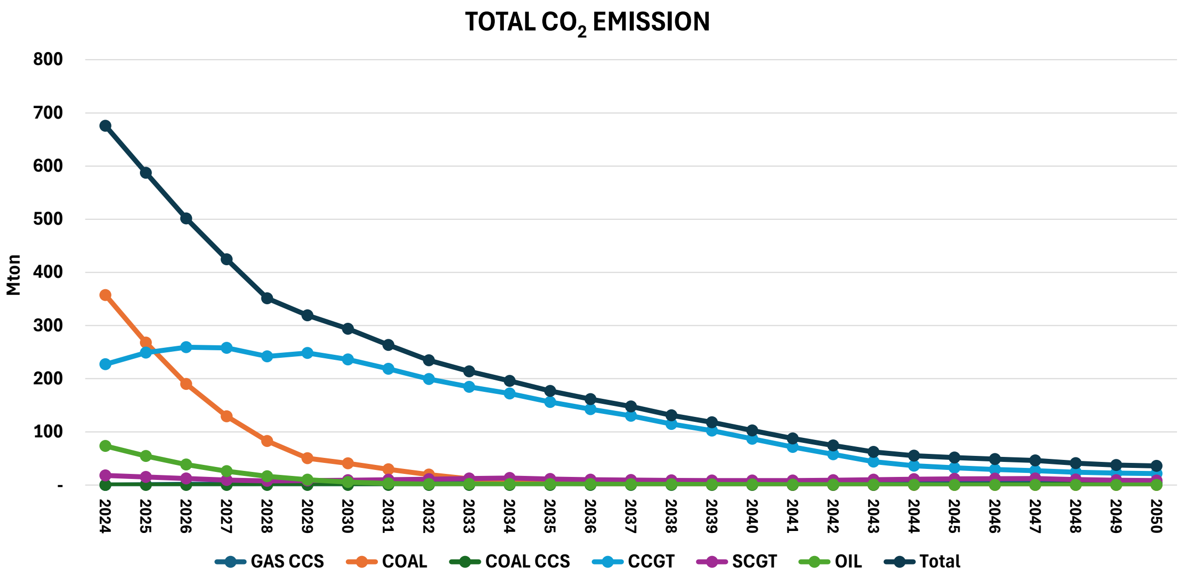

Figure 7.20: APS Scenario Total CO_2 Emission

The analysis of the evolution of total CO_2 emissions in Figure 7.20 highlights the effectiveness of the APS scenario in leading the European power system toward deep decarbonization by 2050. The 680 Mton emitted in 2024 drops drastically to a residual value of approximately 35 Mton in 2050. The primary driver of this contraction in the first decade is the rapid phase-out of coal, whose emissions reduce almost to zero by 2033, alongside the phase-out of fuel oil by 2030. In this context, natural gas (CCGT) plays a key role as a transition technology. Indeed, the graph shows a slight initial increase in emissions, peaking at approximately 260 Mton in 2027 specifically to replace the decommissioning of heavier fossil fuels, followed by a steady decline due to both the end-of-life of existing plants and their progressive replacement by renewable sources. A relevant aspect of the graph is the impact of carbon capture technologies: although the model anticipates investments in Gas CCS and, in the final phase, in Coal CCS, their direct emissions remain extremely contained, demonstrating the capability of these technologies to ensure system stability without increasing the emission balance. At the end of the time horizon, the residual 35 Mton reflects the marginal and strictly necessary use of gas plants during moments of low renewable production to cover winter and summer peaks.

7.3. Net Zero Emissions (NZE) Scenario: A Normative Pathway

The following sections provide a detailed analysis of the primary outputs generated by the NZE 2050 scenario simulation. The discussion focuses specifically on the evolution of New Capacity and Total Capacity, the dynamics of electricity Production, and the trajectory of CO_2 emissions generated by the system throughout the modelled time horizon.

New Capacity, Total Capacity and Production Analysis

Table 7.9: NZE Scenario New Installed Capacity

New Capacity [GW]	BATT	PHES	BIO	GAS CCS	ROR	CCGT	SCGT	NUC	PV	WIND OFF	WIND ON
2024	0.75	-	-	-	-	-	-	-	-	-	-
2025	1.89	3.00	5.00	3.00	-	6.00	2.00	5.00	109.20	14.27	6.57
2026	-	3.00	5.00	-	-	-	-	5.00	110.00	23.56	40.00
2027	-	3.00	5.00	-	-	-	-	5.00	19.67	30.00	40.00
2028	-	3.00	5.00	-	-	0.67	-	5.00	-	30.00	40.00
2029	-	3.00	5.00	-	-	5.41	-	5.00	110.00	30.00	40.00
2030	0.34	3.00	5.00	-	-	-	-	5.00	120.00	40.00	50.00
2031	0.96	2.00	5.00	-	-	-	-	5.00	120.00	50.00	50.00
2032	2.83	2.00	5.00	-	-	-	-	5.00	120.00	50.00	50.00
2033	-	2.00	5.00	3.74	-	-	0.47	5.00	120.00	50.00	50.00
2034	13.44	2.00	5.00	5.00	-	-	2.00	5.00	11.38	50.00	50.00
2035	13.02	2.00	5.00	5.00	-	-	2.00	7.00	-	60.00	60.00
2036	15.61	2.00	5.00	5.00	-	-	-	7.00	52.97	60.00	60.00
2037	20.63	2.00	5.00	0.11	-	-	-	7.00	12.34	60.00	60.00
2038	21.19	2.00	5.00	-	-	-	-	7.00	116.48	60.00	60.00
2039	21.17	2.00	5.00	-	-	-	-	8.00	130.00	60.00	60.00
2040	20.65	2.00	7.00	-	-	-	-	8.00	43.40	60.00	60.00
2041	18.76	2.00	7.00	-	-	-	-	8.00	-	60.00	60.00
2042	18.70	2.00	7.00	-	-	-	-	8.00	-	60.00	60.00
2043	18.28	2.00	7.00	-	-	-	-	8.00	43.76	60.00	60.00
2044	17.59	2.00	7.00	-	-	-	-	8.00	130.00	60.00	60.00
2045	13.58	2.00	7.00	-	-	-	-	10.00	118.81	70.00	60.00
2046	10.02	2.00	10.00	-	-	-	-	10.00	130.00	70.00	60.00
2047	10.51	2.00	10.00	-	-	-	-	10.00	130.00	70.00	60.00
2048	24.20	2.00	10.00	-	-	-	-	12.00	0.24	70.00	60.00
2049	25.77	2.00	10.00	-	-	-	-	12.00	67.58	70.00	60.00
2050	28.63	3.00	10.00	-	7.40	-	-	12.00	130.00	70.00	60.00

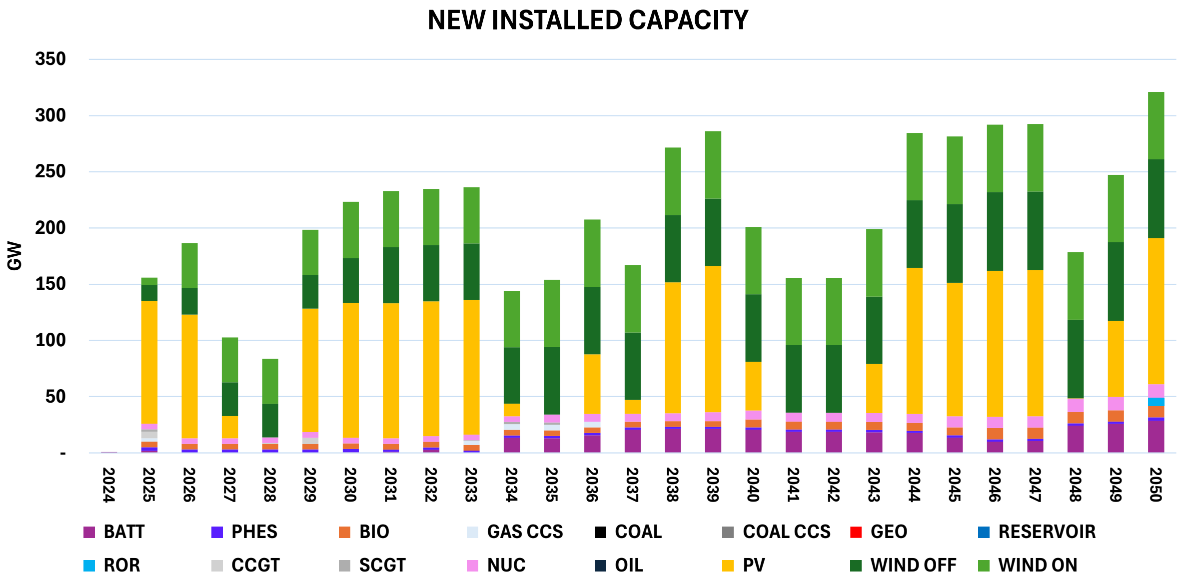

Figure 7.21: NZE Scenario New Installed Capacity

Table 7.10: NZE Scenario Total Installed Capacity

Total Capacity [GW]	BATT	PHES	BIO	GAS CCS	COAL	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	11.85	28.90	45.11	-	152.02	73.20	227.93	75.98	116.10	29.50	363.97	35.67	246.19
2025	13.74	31.90	50.11	3.00	147.78	73.20	233.85	77.15	121.10	29.18	473.16	49.94	252.76
2026	13.74	34.90	55.11	3.00	141.63	73.20	233.69	76.03	126.09	28.74	583.16	73.49	292.76
2027	13.74	37.90	60.11	3.00	133.24	73.20	233.42	74.55	131.09	28.17	602.81	103.49	332.76
2028	13.74	40.90	65.10	3.00	122.47	73.20	233.61	72.65	136.07	27.43	602.78	133.49	372.76
2029	13.63	43.90	70.10	3.00	109.50	73.20	238.21	70.28	141.05	26.51	712.74	163.49	412.76
2030	13.93	46.90	75.08	3.00	94.81	73.20	236.91	67.41	146.01	25.40	832.66	203.49	462.76
2031	14.79	48.90	80.05	3.00	79.18	73.20	234.89	64.01	150.95	24.08	952.54	253.49	512.76
2032	17.37	50.90	85.01	3.00	63.55	73.20	231.89	60.11	155.83	22.56	1,072.35	303.49	562.76
2033	16.88	52.90	89.94	6.74	48.86	73.20	227.59	56.23	160.66	20.87	1,192.07	353.49	612.74
2034	29.46	54.90	94.83	11.74	35.89	73.20	221.67	53.49	165.38	19.03	1,203.02	403.49	662.71
2035	41.21	56.90	99.67	16.74	25.13	73.20	213.85	50.49	171.96	17.09	1,202.38	463.49	722.62
2036	55.21	58.90	104.43	21.74	16.73	73.20	203.91	45.34	178.35	15.09	1,254.44	523.49	782.43
2037	74.10	60.90	109.09	21.84	10.58	73.20	191.78	40.20	184.46	13.10	1,265.48	583.49	842.03
2038	93.68	62.90	113.61	21.84	6.34	73.20	177.55	35.19	190.23	11.15	1,380.17	643.49	901.23
2039	112.84	64.90	117.96	21.84	3.60	73.20	161.52	30.46	196.55	9.31	1,507.74	703.49	959.75
2040	130.74	66.90	124.10	21.84	1.94	73.20	144.15	26.10	202.35	7.62	1,547.90	763.49	1,017.16
2041	149.00	68.90	130.00	21.84	0.98	73.20	126.08	22.20	207.51	6.11	1,543.68	823.49	1,072.90
2042	167.45	70.90	135.63	21.84	0.47	73.20	108.01	18.80	211.98	4.79	1,538.29	883.49	1,126.32
2043	185.63	72.90	140.96	21.84	0.21	73.20	90.64	15.93	215.68	3.67	1,575.31	943.47	1,176.75
2044	203.17	74.90	145.99	21.84	0.09	73.20	74.61	13.56	218.61	2.75	1,697.04	1,003.44	1,223.70
2045	216.40	76.90	150.72	21.84	0.04	73.20	60.38	11.66	222.79	2.02	1,805.93	1,073.35	1,266.97
2046	225.46	78.90	158.20	21.84	0.01	73.20	48.25	10.19	226.28	1.44	1,924.24	1,143.14	1,306.80
2047	233.14	80.90	165.45	21.84	0.01	73.20	38.32	9.06	229.21	1.01	2,040.76	1,212.68	1,343.97
2048	257.34	82.90	172.54	21.84		73.20	30.49	8.24	233.73	0.69	2,025.77	1,281.79	1,379.67
2049	269.67	84.90	179.56	21.84	-	73.20	24.57	7.65	238.05	0.46	2,076.49	1,350.24	1,415.37
2050	285.29	87.90	186.57	21.84	-	80.60	20.27	5.23	242.37	0.30	2,188.20	1,417.83	1,445.96

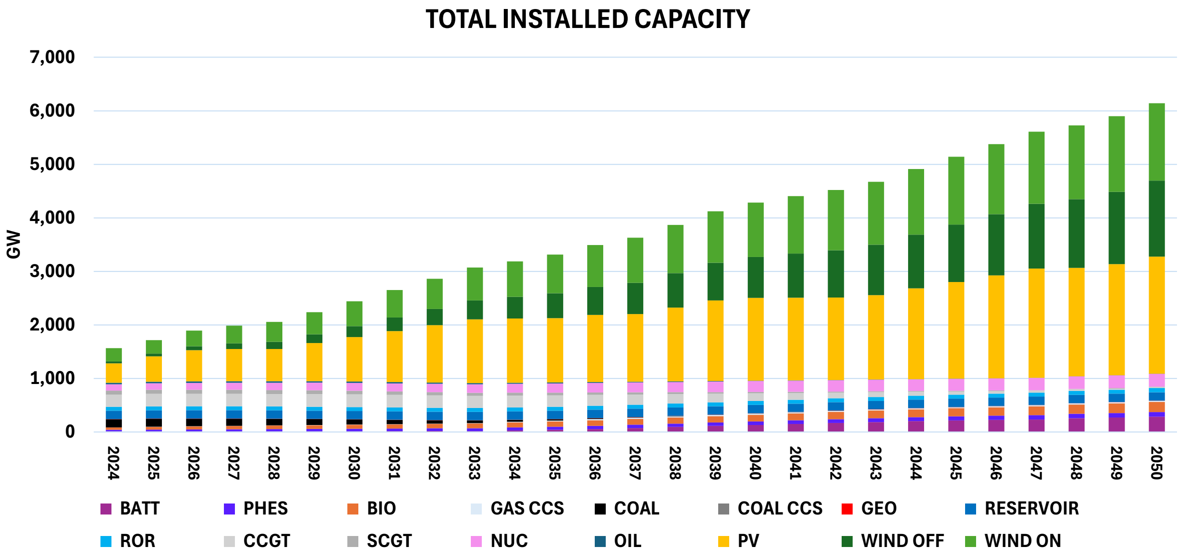

Figure 7.22: NZE Scenario Total Installed Capacity

Table 7.11: NZE Scenario Total Net Electricity Production

Production [TWh]	BATT	PHES	BIO	GAS CCS	COAL	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	2.5	2.1	191.9	-	434.0	24.2	374.0	292.6	654.4	34.4	742.0	102.4	384.9	99.9	519.2
2025	0.7	2.4	182.3	23.7	346.5	24.2	374.0	293.2	719.8	35.8	795.6	51.2	500.4	139.9	533.0
2026	3.9	6.0	173.2	23.7	166.3	24.2	374.0	293.2	791.8	22.2	875.2	24.6	616.7	195.8	617.3
2027	9.5	44.1	164.5	23.7	74.8	24.2	374.0	293.2	866.0	24.4	918.7	11.1	637.5	274.2	701.7
2028	14.1	80.8	156.3	13.7	71.2	24.2	374.0	293.2	804.7	26.9	1,010.5	4.8	637.4	373.9	786.0
2029	10.0	67.4	148.5	13.1	56.1	24.2	374.0	293.2	781.0	29.6	960.0	2.3	753.7	457.9	855.8
2030	10.8	76.6	141.1	13.1	38.2	24.1	374.0	293.2	728.7	32.5	902.8	2.3	856.5	570.0	953.4
2031	12.1	91.2	134.0	11.9	20.3	24.1	374.0	293.2	669.3	35.8	834.2	2.2	1,007.3	708.4	996.6
2032	14.3	104.6	127.3	11.2	15.5	24.0	374.0	292.6	618.3	31.0	767.2	2.4	1,120.6	833.4	1,075.7
2033	13.5	123.9	120.9	25.0	11.2	24.0	374.0	292.0	556.8	24.7	703.2	2.6	1,237.8	968.7	1,135.0
2034	19.0	121.2	114.9	42.4	7.9	23.9	374.0	291.4	527.1	21.8	686.0	2.7	1,240.3	1,121.1	1,199.7
2035	35.1	96.7	109.2	60.1	4.3	23.9	373.3	290.8	478.6	17.0	687.5	1.3	1,219.2	1,276.1	1,283.6
2036	51.9	67.0	103.7	78.0	1.8	23.8	372.5	290.2	411.9	10.4	695.8	1.2	1,229.5	1,462.3	1,314.0
2037	58.3	53.1	98.5	77.3	1.1	23.8	371.8	289.7	371.1	6.3	715.6	1.4	1,187.3	1,588.4	1,442.7
2038	62.0	63.4	93.6	75.7	0.7	23.7	371.0	289.1	294.5	5.5	721.7	1.2	1,267.3	1,774.3	1,442.2
2039	77.8	77.9	88.9	75.6	0.4	23.7	370.3	288.5	213.0	5.4	727.0	1.0	1,460.6	1,860.2	1,437.6
2040	90.9	91.6	84.5	75.6	0.4	23.6	369.6	288.1	162.8	4.8	748.3	1.4	1,407.3	2,033.1	1,542.9
2041	118.6	110.8	80.2	74.3	0.2	23.6	368.8	288.5	129.0	4.1	780.7	1.1	1,453.3	2,211.3	1,495.9
2042	131.7	116.0	76.2	65.2	0.1	23.5	368.1	289.1	113.3	3.5	798.9	0.9	1,417.1	2,330.5	1,606.5
2043	144.8	115.0	72.4	48.9	0.0	23.5	367.3	289.7	98.3	2.9	802.4	0.7	1,497.2	2,528.9	1,552.1
2044	161.3	106.6	70.8	47.9	0.0	23.5	366.6	290.2	76.2	2.5	754.0	0.5	1,514.4	2,661.3	1,648.1
2045	175.3	96.5	67.3	46.0	0.0	23.4	365.9	290.8	59.7	2.1	703.7	0.4	1,775.0	2,779.7	1,560.6
2046	188.0	89.3	73.2	45.2	0.0	23.4	365.1	291.4	34.9	1.9	652.1	0.3	1,771.8	2,938.8	1,615.5
2047	201.3	83.1	84.2	43.8	0.0	23.3	364.4	292.0	8.5	1.7	602.3	0.3	1,860.6	3,109.7	1,590.9
2048	239.7	76.8	92.2	42.1	-	23.3	363.7	292.6	0.6	0.1	594.7	0.2	1,869.6	3,280.0	1,622.7
2049	240.8	73.4	92.2	39.5	-	23.2	363.0	293.2	0.0	0.0	571.2	0.0	1,779.5	3,643.0	1,602.9
2050	246.9	89.1	96.9	0.5	-	23.2	362.2	293.7	0.0	0.0	540.5	-	1,981.9	3,629.5	1,578.2

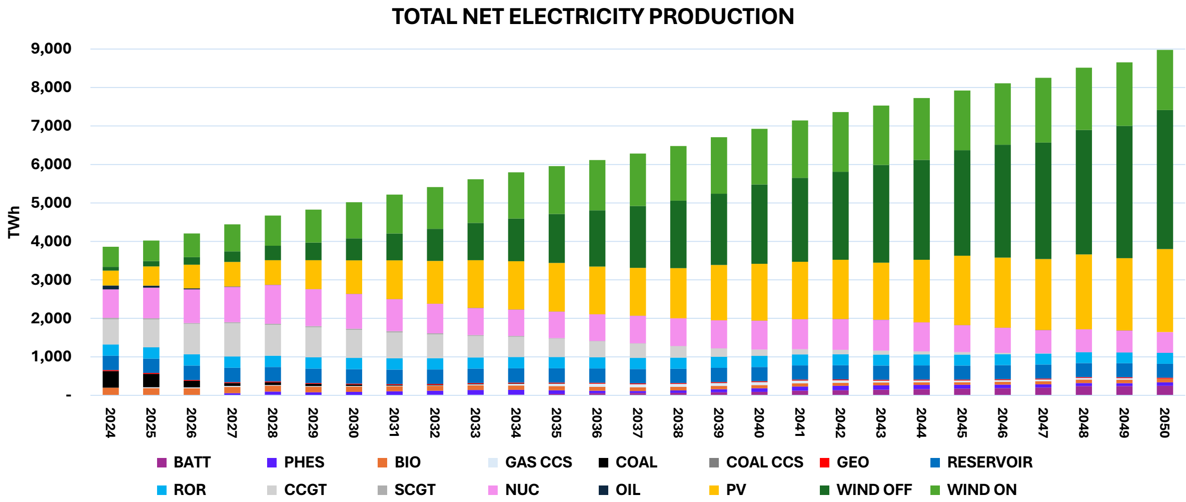

Figure 7.23: NZE Scenario Total Net Electricity Production

Table 7.12 NZE Scenario Capacity Factor

Year	BIO	GAS CCS	COAL	COAL CCS	GEO	RESERVOIR	ROR	CCGT	SCGT	NUC	OIL	PV	WIND OFF	WIND ON
2024	0.49	-	0.33	-	0.81	0.27	0.46	0.33	0.05	0.73	0.40	0.12	0.32	0.24
2025	0.42	0.90	0.27	-	0.81	0.27	0.46	0.35	0.05	0.75	0.20	0.12	0.32	0.24
2030	0.21	0.50	0.05	-	0.81	0.27	0.46	0.35	0.06	0.71	0.01	0.12	0.32	0.24
2035	0.13	0.41	0.02	-	0.80	0.27	0.45	0.26	0.04	0.46	0.01	0.12	0.31	0.20
2040	0.08	0.39	0.02	-	0.79	0.27	0.45	0.13	0.02	0.42	0.02	0.10	0.30	0.17
2045	0.05	0.24	0.02	-	0.79	0.27	0.45	0.11	0.02	0.36	0.02	0.11	0.30	0.14
2050	0.06	0.00	-	-	0.78	0.27	0.42	0.00	0.00	0.25	-	0.10	0.29	0.12

The analysis of the New Capacity output for the Net Zero Emissions (NZE) scenario, reported in Table 7.9 and Figure 7.21, reveals that the model exhibits a strongly discontinuous behaviour in terms of newly installed capacity. The observed discontinuity in the new capacity installation curve, compared to previously analysed scenarios, is primarily driven by a combination of interconnected factors. This behaviour stems from the assumed higher upper limits on maximum annual investments which, given the model's 'just-in-time' logic to minimize the objective function, enabled greater flexibility to concentrate investments during the most cost-effective periods. This flexibility is further exploited due to the assumed aggressive cost reductions in renewables, most notably offshore wind, which is assumed to reach CAPEX parity with onshore wind by 2050, triggering massive capacity additions once specific economic thresholds are reached.

Specifically, it is observed in Table 7.9 that the model tends to saturate the installable capacity for onshore wind from 2026 through 2050. In 2025, it installs only what is necessary to cover residual demand, as the model has already saturated the installation of more economically convenient technologies for that year. A similar trend applies to offshore wind; the model tends to saturate the maximum installable capacity starting from 2027, as evident in Table 7.9. For the years 2025 and 2026, the model installs the maximum allowed amount, having reached the constraint for the maximum annual percentage increase in production (+40% per year).

In 2025, the model installs the maximum capacity for all technologies for favouring the decommissioning of coal and oil and to meet the rapidly increasing electricity demand, as evident in Table 7.9. Furthermore, in 2025, it installs the maximum available capacity for Solar PV, as this technology reached its maximum annual percentage production increase constraint (+30% per year).

Regarding Solar PV, a strongly discontinuous behaviour in new installed capacity is observed in Table 7.9 and Figure 7.21, primarily due to the mix of factors previously listed. The main reason for this trend is linked to the adoption of a higher total max capacity investment for this technology, symbolizing the greater climate ambition of the scenario, which consequently allowed the model more freedom in choosing when to install the capacity necessary for the transition. Indeed, as observed in previous scenarios, the model consistently tends to postpone investments to install the maximum possible capacity "just in time" rather than favouring gradual and less discontinuous solutions. This is mainly because this approach reduces the objective function by increasing the salvage value and decreasing the discounted investment costs of the technology. Additionally, the model shows a strong preference for wind over solar; this is because wind is assumed to have a proportionally greater cost reduction, higher capacity factors, and the ability to produce during evening peaks when PV is inactive. Between 2034 and 2036, the model tends to saturate the maximum available capacity for Gas with CCS (Table 7.9), largely due to the sharp decline in installed capacity for conventional CCGTs reaching their end-of-life. This same reason drives the installation of SCGTs during those same years.

For the years 2026 and 2027, the model also tends to saturate the maximum allowed percentage increase for CCGT electricity production (+10% per year), which is necessary for favouring the phase-out of coal and oil, as in Table 7.11. From 2027 to 2031, the model similarly saturates the maximum percentage increase for SCGT (+10% per year).

Furthermore, the model demonstrates the necessity of installing the maximum possible capacity in technologies such as biomass and nuclear from the beginning of the simulation, as in Table 7.9. This is required to manage demand peaks, particularly in the final years of the transition, where it must face sharply rising electricity demand, peaks concentrated in the same time intervals, a strictly decreasing emission limit, an increasing carbon tax, and zero maximum capacity investment constraints for conventional gas from 2035, a year in which conventional gas also experiences a strong reduction in residual installed capacity due to plant retirements, as evident in Table 7.10. To address these challenges, the model reacts by installing as much biomass and nuclear as possible early on. These technologies are subsequently used only for peak management, as evidenced by the sharp reduction in their Capacity Factors (Table 7.12) and their decreasing percentage of total electricity production (Table 7.11), despite this massive increase in installed capacity (Table 7.10).

From the analysis of production and technology Capacity Factors (Table 7.12), it is observed that nuclear, CCGT, and Gas with CCS are utilized with significantly high CFs during the early years of the transition (approximately 2025–2030). These values are notably higher than those recorded in 2024, underscoring that these technologies effectively offset the production load left by the rapid decommissioning of coal and oil assets, alongside the reduction of biomass, which was penalized by the absence of a thermal sector and lower electrical efficiency.

These technologies also cover an electricity demand that is even higher than in the previous two scenarios analysed. Moreover, between 2046 and 2050, there is an increase in electricity production from biomass as in Table 7.11; this shows that the imposition of a higher carbon tax and the phase-out of conventional gas (with the stop on new investments from 2035 onwards) favoured the use of greener technologies.

Analysing production from coal and oil in Table 7.11, these techs decrease more rapidly than in the APS scenario (Table 7.7), proving that higher carbon taxes primarily impact the most emissive technologies, even though the NZE scenario considers a falling fuel price trajectory for gas, coal, and oil. Conversely, electricity production from CCGT and SCGT in the early transition years (2030–2035) (Table 7.11) is higher than in the intermediate APS scenario (Table 7.7), mainly due to reduced fuel costs, the need to meet rising demand, and the requirement to fill the higher gap left by coal and oil.

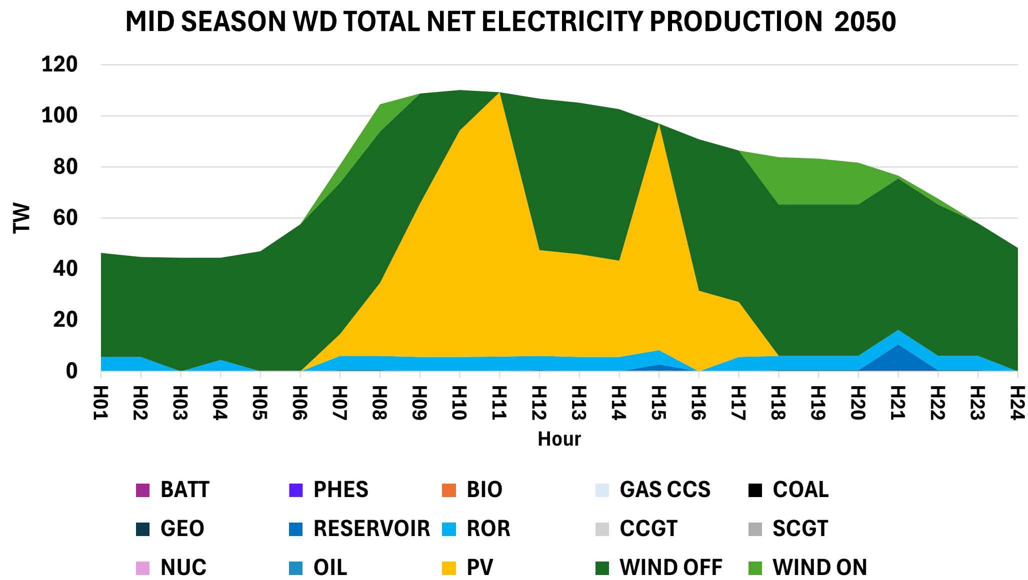

Figure 7.24: NZE Mid-Season Workday Total Net Electricity Production 2050

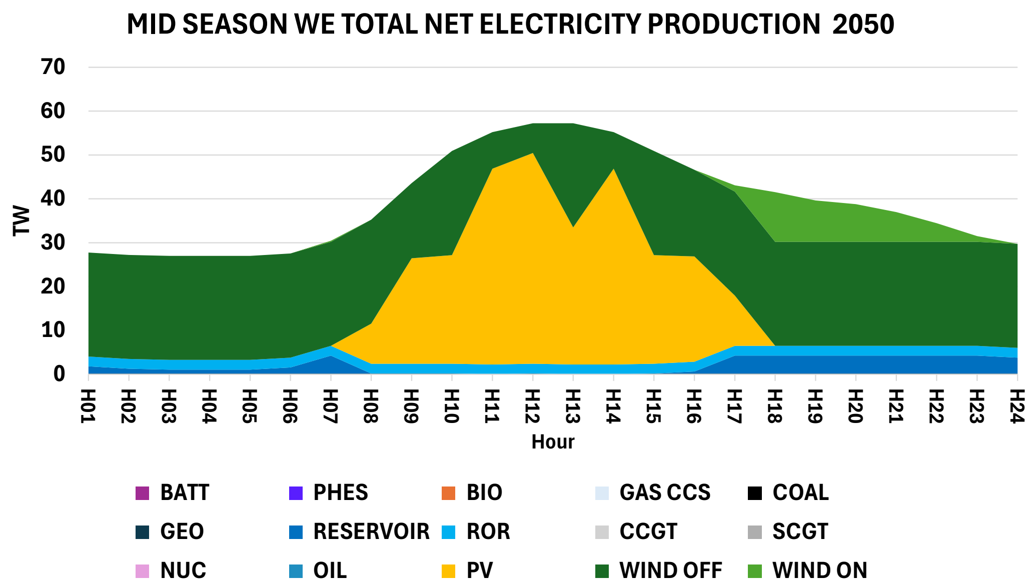

Figure 7.25: NZE Mid-Season Weekend Total Net Electricity Production 2050

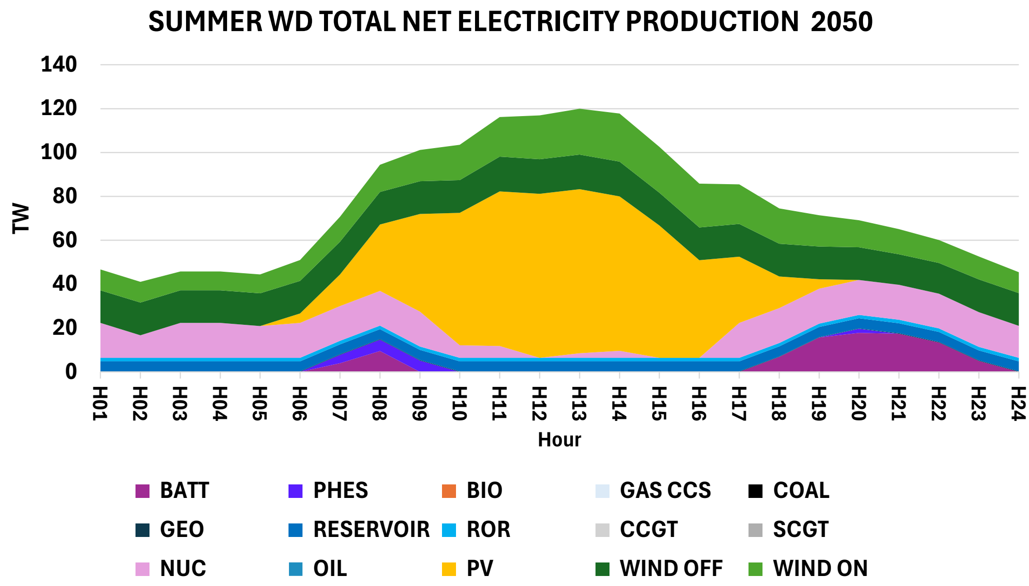

Figure 7.26: NZE Summer Workday Total Net Electricity Production 2050

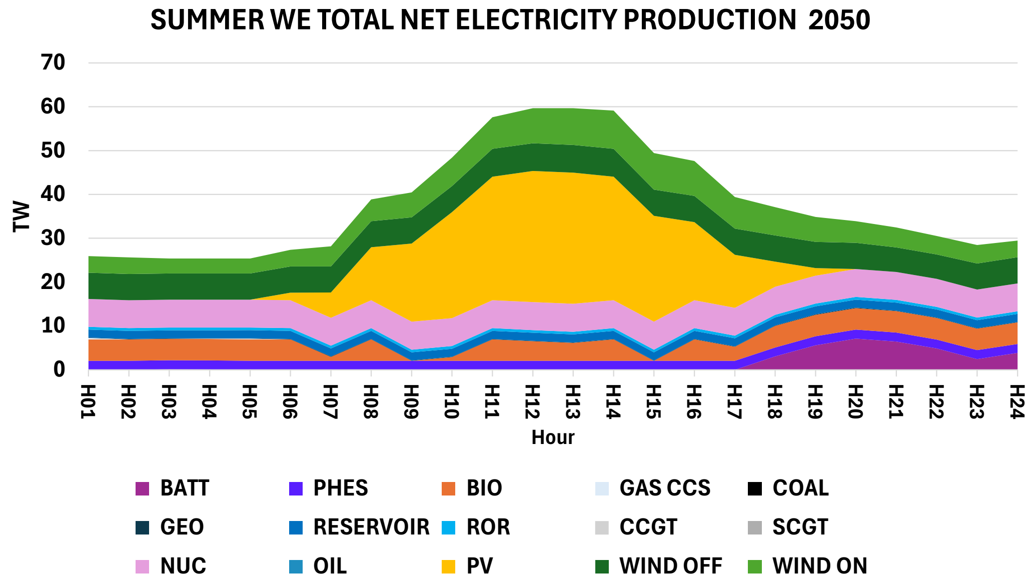

Figure 7.27: NZE Summer Weekend Total Net Electricity Production 2050

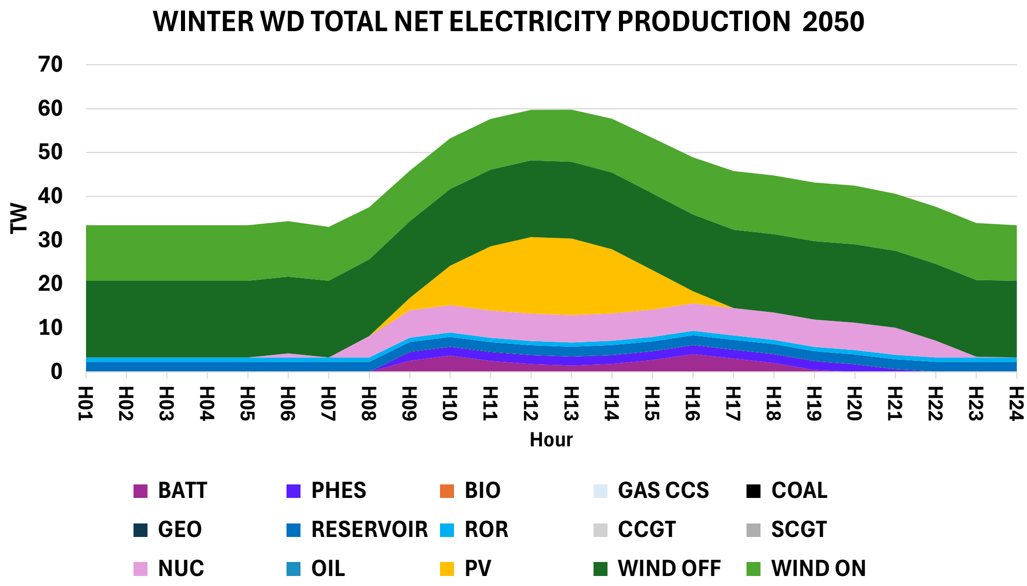

Figure 7.28: NZE Winter Workday Total Net Electricity Production 2050

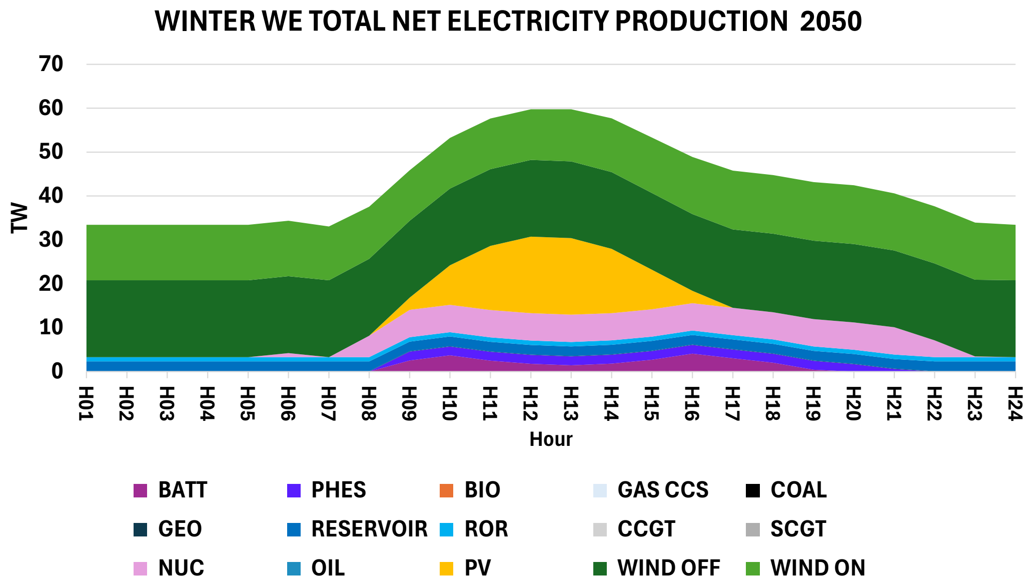

Figure 7.29: NZE Winter Weekend Total Net Electricity Production 2050

The analysis of the 2050 production profiles across various time slices reveals that during the mid-season, the system can satisfy demand directly through renewable generation without requiring storage intervention, as in Figure 7.24 and Figure 7.25. In this period, the model does not initiate charging or discharging cycles for batteries or Pumped Hydro Storage (PHS).

Conversely, during summer workdays, the model relies on both batteries and PHS to manage the morning and evening demand peaks, as evident in Figure 7.26.

Specifically, battery charging occurs in two distinct phases: from 1 to 4 and again from 11 to 16. The prominent production peak observed at 11 in Figure 7.26 is directly associated with the intensive charging phase of the battery system. During summer weekends, the model focuses on charging battery storage between 8 and 17, followed by a discharge phase from 18 to 24 to cover the evening load, as evident in Figure 7.27.

The winter season displays a more complex pattern, with multiple production peaks driven by the simultaneous charging of batteries and PHS. On winter workdays (Figure 7.28), battery charging is concentrated between 1 and 6; notably, a temporary reduction in charging intensity at 4 explains the observed "valley" in the production profile. During this same early morning, PHS units are also charged. A second charging cycle occurs later in the day, with batteries being charged from 12 to 14 and PHS from 11 to 19. In this configuration, batteries are strategically discharged to mitigate both the morning and evening demand peaks, while PHS discharge is primarily utilized during the weekends, as in Figure 7.29. On winter weekends, the model prioritizes battery charging from 1 to 7, followed by a sustained discharge phase for both batteries and PHS between 8 and 20 to support the system load.

Finally, the systematic difference in production levels between workdays and weekends is primarily a function of the temporal weighting within the model. Since workdays represent 5/7 of a week compared to the 2/7 allocated to weekends, the aggregated activity and production values are proportionally higher, reflecting the greater cumulative energy demand and operational intensity of the working week.

Analysing the 2050 production by time slices, the same pattern seen in the previous scenarios emerges: during the mid-season, the model satisfies demand using only renewables, whereas in the winter and summer seasons, it has to rely on batteries and firm dispatchable technologies to cover peaks. However, in this scenario, given the higher penetration of renewables (especially in terms of wind capacity), there is no need for batteries during the mid-season. Batteries and Pumped Hydro (PHES) are utilized solely for managing the winter and summer seasons.

A fundamental aspect to underline is the significantly higher renewable curtailment in this scenario, as evident in Table 7.12. While it has been previously noted that OSeMOSYS tends to underestimate batteries and prefer other technologies for peak coverage, the analysis of production by time slices suggests that rather than focusing on daily batteries, which certainly assist with daily dispatch, the key lies in Long-Duration Energy Storage (LDES). This is evident for two reasons:

- The model tends to saturate the maximum installable capacity constraint for Pumped Hydro.

- The model exhibits heavy curtailment of wind power, which is installed to cover peaks but is disconnected during mid-season periods when the model utilizes other sources.

The fact that the model does not require onshore wind during the mid-season (Figure 7.24, Figure 7.25) highlights that if other technologies, such as electrolyzers and fuel cells, had been included, the model would have had an alternative pathway to manage winter and summer peaks through seasonal storage.

CO_2 Emissions Curve Analysis

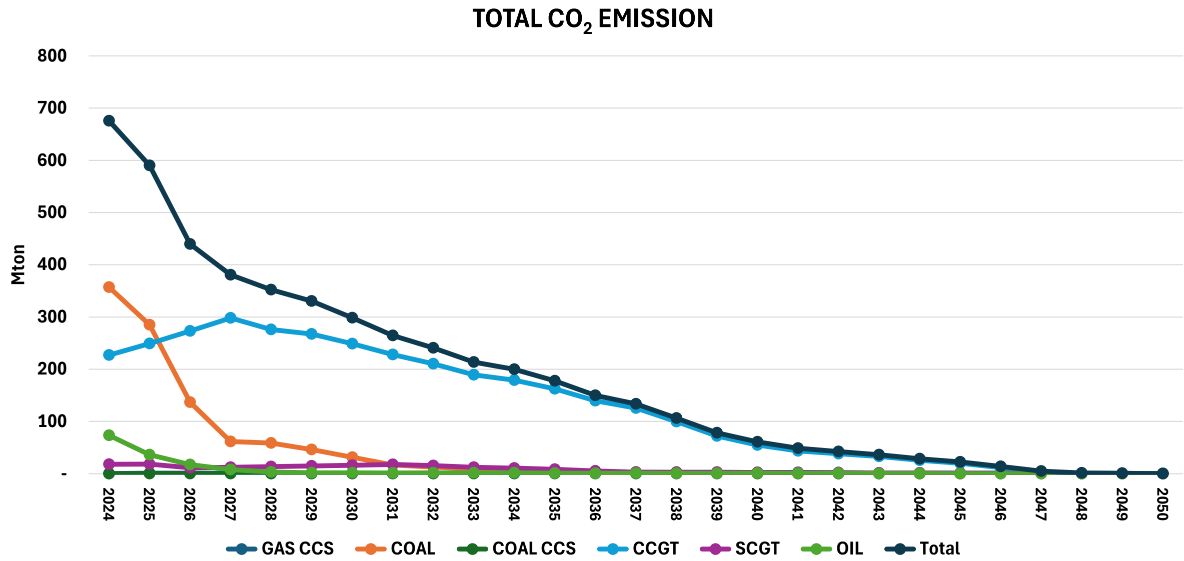

Figure 7.30: NZE Scenario Total CO_2 Emission

The analysis of the total CO_2 emissions trajectory (Figure 7.30) between 2024 and 2050 highlights a deep and aggressive decarbonization pathway for the Net Zero (NZE) scenario, ending in a carbon-neutral state for the power system by 2049–2050. Starting from an initial value of approximately 680 Mton in 2024, the system undergoes a rapid structural shift characterized by the vertical collapse of coal-related emissions, which decrease from roughly 360 Mton to a near-total phase-out by 2036.

During the first decade, CCGT (Combined Cycle Gas Turbine) emerges as a critical gap technology; its emissions experience a strategic peak of approximately 300 Mton in 2027 as it temporarily compensates for the rapid decommissioning of coal and oil assets.

Crucially, while the NZE scenario is modelled with an imposed linear trajectory as a formal emission constraint, the resulting output curve exhibits an almost exponential reduction pattern, as evident in Figure 7.30. This behaviour indicates that the internal economic and technical drivers of the model, such as the increasing carbon tax, the rapid decline in renewable capital costs, the technical obsolescence of the existing fleet, and the constraint on total annual max capacity investment, force the system to decarbonize at a pace that significantly exceeds the minimum linear requirement in the early and middle stages of the transition. Ultimately, this profile demonstrates a successful transition where market-driven pressures and technological evolution lead to the elimination of all fossil fuel-based CO_2 output, achieving a fully carbon-neutral generation mix.

7.4. Comparative Analysis: OSeMOSYS Outputs vs. World Energy Outlook Scenarios

This section provides a detailed comparative analysis between the model results and the IEA World Energy Outlook (WEO) 2024 outputs for continental Europe. It is important to first emphasize that this benchmarking is restricted to the Stated Policies (STEPS) and Announced Pledges (APS) scenarios, as the WEO has not released detailed regional annexes or specific results for the European Net Zero Emissions by 2050 (NZE) scenario.

Furthermore, the aim of this comparison is focused on specific categories where direct alignment is possible, namely total electricity production decomposed by primary energy sources. This limitation is due to the absence of other granular data results for the European region within the WEO documentation. A direct comparison of CO_2 emissions is also omitted, as the figures reported by the WEO are not exclusive to the power sector but include thermal and other emissive industries, making an assessment of the electricity generation CO_2 emissions impossible.

From a methodological perspective, before conducting the comparison, a fundamental step is required to harmonize the datasets: OSeMOSYS outputs are converted from net to gross values by incorporating the contribution of own use (auxiliary loads). Following this adjustment, a consistent benchmarking of the results is achieved. Ultimately, the analysis of these comparisons between the WEO 2024 projections and the OSeMOSYS outputs serves to address the first research question of this study:

Research Question 1: ‘Can a simplified, aggregated linear optimization model, focused solely on cost minimization, produce trends and outputs consistent with those of the IEA WEO 2024 Europe scenarios given a consistent set of input parameters?’

The findings suggest that while the model successfully replicates macro-trends by 2050 with high accuracy, it exhibits significant discrepancies in intermediate trajectories due to the fundamental differences between a deterministic optimization framework and a policy-driven simulation model.

7.4.1. Stated Policies Scenario

Table 7.13: Comparison STEPS Scenario Results: WEO 2024 vs OSeMOSYS

Stated Policy Scenario	WEO	OSeMOSYS	WEO	OSeMOSYS	WEO	OSeMOSYS
Year	2030	2030	2035	2035	2050	2050
Total Elec. Generation (TWh)	4,719	4,579	5,508	5,073	6,893	6,617
Coal Elec. Generation (TWh)	281	54	201	4	167	-
Gas Elec. Generation (TWh)	495	938	331	794	206	600
Nuclear Elec. Generation (TWh)	779	907	765	649	834	588
Fossil Elec. Generation (TWh)	1,555	1,908	1,297	1,448	1,207	1,188
Renewable Elec. Generation (TWh)	3,118	2,671	4,178	3,624	5,673	5,428
Wind Elec. Generation (TWh)	1,209	1,016	1,844	1,559	2,687	2,395
PV Elec. Generation (TWh)	871	829	1,226	1,247	1,638	2,294

The analysis of the Stated Policies (STEPS) scenario in Table 7.13 reveals a systematic underestimation of total electricity generation in the OSeMOSYS model compared to the WEO 2024 projections: specifically, 3% in 2030, 8% in 2035, and 4% in 2050. These discrepancies are primarily linked to differing assumptions regarding the evolution of electricity demand and the specific performance parameters of modelled technologies. Specifically, while OSeMOSYS assumes a linear growth profile for electricity demand between 2024 and 2050, the percentage gaps suggest that the WEO 2024 utilizes a more complex, non-linear growth trajectory that does not perfectly coincide with the model's simplified assumptions.

A defining feature of the OSeMOSYS output is the accelerated and aggressive phase-out of coal, which is replaced by a significantly higher reliance on natural gas compared to WEO projections. This rapid transition is largely driven by a modelling choice: in the absence of regionalized projections, the EU carbon tax trajectory is applied to the entire European continent. The resulting economic pressure forced the solver to phase-out coal in favour of gas-fired generation, identified as the most cost-effective fuel, far earlier than the gradual decline projected by the IEA.

The nuclear trajectory in OSeMOSYS differs notably from the WEO trend. In the model, nuclear generation sees a sharp initial increase during the early years of the transition to facilitate the rapid decommissioning of coal and oil assets. However, a shift occurs toward the end of the horizon: despite installed capacity reaching its peak in 2050, actual nuclear electricity production declines. As previously analysed, the model prioritizes renewable dispatch due to near-zero marginal costs, effectively relegating nuclear units to a role of firm capacity, providing system stability rather than baseload energy.

The renewable sector displays mixed alignment:

- Wind (Onshore & Offshore): The growth trend remains broadly consistent with WEO data. While OSeMOSYS exhibits lower production levels in 2030 and 2035, it successfully "recovers" this gap by the end of the 2050 horizon.
- Solar PV: Production remains closely aligned with WEO projections through 2035. However, by 2050, the model registers a massive increase in solar output, significantly exceeding WEO estimates as the optimization identifies PV as the primary cost-effective technology for long-term decarbonization.

Despite these granular variances, OSeMOSYS proves remarkably robust when results are aggregated into macro-categories. By 2050, the model represents the broad European energy mix with high accuracy, underestimating fossil fuel production by only 1.5% and total renewable production (including other zero-carbon resources) by just 4% compared to WEO 2024 benchmarks.

7.4.2. Announced Pledges Scenario

Table 7.14: Comparison APS Scenario Results: WEO 2024 vs OSeMOSYS

Announced Pledges Scenario	WEO	OSeMOSYS	WEO	OSeMOSYS	WEO	OSeMOSYS
Year	2030	2030	2035	2035	2050	2050
Total Elec. Generation (TWh)	5,027	4,878	6,059	5,638	8,174	7,948
Coal Elec. Generation (TWh)	180	54	97	5	56	31
Gas Elec. Generation (TWh)	476	780	251	608	73	315
Nuclear Elec. Generation (TWh)	795	889	802	664	1,172	906
Fossil Elec. Generation (TWh)	1,451	1,732	1,150	1,313	1,301	1,251
Renewable Elec. Generation (TWh)	3,540	3,146	4,888	4,325	6,846	6,697
Wind Elec. Generation (TWh)	1,441	1,229	2,297	1,931	3,540	3,273
PV Elec. Generation (TWh)	1,021	1,063	1,438	1,577	1,863	2,685

The analysis of the Announced Pledges Scenario (APS) demonstrates a systematic underestimation of total electricity generation in the OSeMOSYS model relative to the WEO 2024 projections: 3% in 2030, 7% in 2035, and 3% in 2050. This divergence is primarily based on differing assumptions regarding electricity demand evolution and technological performance. Specifically, while OSeMOSYS assumes a linear growth profile for electricity demand between 2024 and 2050, the percentage gaps suggest that the WEO 2024 utilizes a more complex, non-linear growth trajectory that does not perfectly coincide with the model's simplified assumptions.

Consistent with the previous scenario, OSeMOSYS underestimates coal production by assuming a more aggressive phase-out. However, this discrepancy is less pronounced in the APS compared to STEPS. Notably, in 2050, OSeMOSYS records a slight increase in coal-fired generation, which is entirely coupled with Carbon Capture and Storage (CCS) technologies.

Conversely, the model significantly overestimates natural gas production compared to the WEO 2024, which projects a drastic reduction in gas reliance. This gap highlights a fundamental difference in modelling priorities: while OSeMOSYS optimizes based on the least-cost solution to decarbonization, the WEO likely incorporates policy aimed at phasing out gas to reduce import dependencies, a strategic move central to European energy security and independence, as reported in (IEA, 2024) and (IEA, 2024).

The behaviour of nuclear energy remains highly variable throughout the simulation. Like the STEPS scenario, OSeMOSYS overestimates nuclear production in 2030 to facilitate the rapid reduction of coal and oil assets. By 2035, however, production is underestimated despite a rise in installed capacity, as nuclear is effectively displaced by lower-marginal-cost renewables that the solver prioritizes for dispatch. While nuclear production undergoes a partial recovery by 2050, it ultimately remains below the levels estimated by the WEO.

In contrast, the growth trend for wind energy, comprising both onshore and offshore contributions, aligns closely with the WEO benchmarks. Although OSeMOSYS exhibits lower wind production levels in the intermediate years of 2030 and 2035, it recovers sufficiently to match the benchmark by the 2050 horizon. Finally, Solar PV output remains highly consistent with WEO projections for 2030 and 2035, followed by a massive surge in 2050. In the final years of the transition, OSeMOSYS identifies Solar PV as a dominant technology of the long-term zero-emission mix, leading to production levels that significantly exceed the IEA's expectations.

When the results are aggregated into macro-categories (Fossil vs. Renewable), the model's ability to mirror the WEO's projected trends improves significantly. By 2050, OSeMOSYS effectively captures the continental European energy landscape, underestimating fossil production by only 3.8% and renewable production (including other zero-carbon sources) by a mere 2%. This confirms that despite granular differences in technology productions, the underlying optimization logic remains highly consistent with global decarbonization targets at an aggregate level.

7.4.3. Divergence Analysis: OSeMOSYS vs. WEO 2024

It is fundamental to emphasize that the OSeMOSYS model, given its nature as a deterministic linear optimization tool with perfect foresight and an objective function focused exclusively on minimizing total discounted system costs, successfully captures with high accuracy the broad macro-division of continental European electricity production by 2050.

Specifically, the model effectively represents the aggregate split between fossil-based and renewable generation at the end of the simulation horizon. However, the model exhibits significant divergences when compared to the IEA World Energy Outlook (WEO) projections regarding individual technological trajectories and intermediate targets. These differences are deeply based on the intrinsic modeling assumptions and varying levels of complexity between a cost-minimizing optimizer and a policy-driven simulation framework.

The following list outlines the primary methodological and structural drivers behind the discrepancies observed between the OSeMOSYS results and the World Energy Outlook (WEO) 2024 projections:

- Deterministic Optimization vs. Simulation Framework: OSeMOSYS is a deterministic optimization model designed to find the mathematical least-cost solution for the entire system. In contrast, the WEO utilizes simulation-based modeling (with partial optimization) to project how energy systems might evolve under specific real-world conditions, reflecting path-dependencies and institutional inertia that a pure optimizer bypasses. In particular, the GEC model adopts a constrained cost-minimization approach rather than a pure least-cost logic to better reflect real-world barriers like policy preferences, capital limits, and technical feasibility. By utilizing a diversified technology portfolio and expert consultation, the analysis ensures a realistic representation of energy sectors and provides a risk hedge, maintaining system resilience even if specific technologies underperform, as reported in (IEA, 2024).
- Perfect Foresight Paradigm: The OSeMOSYS solver operates with "perfect foresight," meaning it considers all future constraints and costs (up to 2050) simultaneously when making decisions in the present. This leads to "just-in-time" capacity expansions and rapid asset retirements that minimize the total discounted cost, whereas the WEO's recursive-dynamic approach is more "anchored" to the simulation year, resulting in a more cautious and gradual transition.
- Cost-Centric Objective Function: The model's objective function is exclusively focused on minimizing discounted system costs, including CAPEX, OPEX, fuel, and carbon taxes. Consequently, it does not inherently account for qualitative strategic factors such as energy security, geopolitical risk, or energy independence, which are often central to the policy-driven scenarios modeled by the IEA, as highlighted in (IEA, 2024).
- Absence of Policy: While the WEO model incorporates specific legislative targets, subsidies, and local phase-out agreements, OSeMOSYS is primarily

driven by the economic cost of the Carbon Tax. Without explicit manual constraints for every local policy, the model chooses the most efficient economic path, explaining the much faster phase-out of coal compared to WEO's projections.

- Technology Polarization vs. Probabilistic Market Allocation: The polarized nature of the OSeMOSYS results, where the solver tends to favour a single technology for a specific role, is an inherent consequence of its Linear Programming (LP) structure, which seeks an absolute deterministic least-cost solution, as reported in (Schrattenholzer, 1991). In contrast, the WEO model utilizes Logit and Weibull functions to determine the market share of various technologies based on their relative cost-competitiveness. While OSeMOSYS identifies a singular "corner solution" that can lead to abrupt and massive shifts in the mix, these probabilistic functions allow the WEO to simulate more realistic technology adoption rates. By weighing specific costs against one another, the WEO represents a market where multiple technologies coexist even if one is marginally more expensive, reflecting the diversity of real-world investors and site-specific conditions that a simplified linear optimizer neglects.
- Geographic Granularity and Regional Diversity: The WEO framework considers a significantly higher number of individual European regions and countries, allowing it to capture localized policies, resource availability, and specific national targets more accurately. OSeMOSYS, operates at a more aggregated level for continental Europe, which may overlook country-specific needs, differences or geographical constraints that lead to the more diversified mix observed in WEO results.
- Technical Operational Constraints: The WEO incorporates high-level complexity regarding the real-world operation of power plants, including ramp rates, minimum stable operating levels, and start-up costs. The inherent simplifications in a standard OSeMOSYS implementation often result in a 'polarized' representation of technological behaviour. The model lacks the 'technical friction' (ramping constraints, minimum stable levels), that would otherwise prevent the near-instantaneous shifts in the generation mix observed in the optimization outputs. This behaviour is particularly evident when analysing production across different time slices. While OSeMOSYS assumes perfect operational flexibility, real-world technologies are subject to physical and technical limitations that constrain such rapid transitions.
- Data Quality and Forecasting Expertise: As an IEA product, the WEO uses a vast array of high-quality primary data and proprietary forecasting tools to

populate its future input variables. The reliance on public datasets for this OSeMOSYS study, while necessary, introduces a degree of uncertainty and a lack of granular market insights that can penalize the model's ability to mirror the projections of the IEA analysts.

7.5. Comparative Synthesis and Cross-Scenario Reflections

This section provides a comparative synthesis of the results obtained across the three modelled scenarios, identifying trends, commonalities, and critical differences. The primary objective of this cross-scenario analysis is to address the second research question:

Research Question 2: Building on the modeling framework established for the benchmarking in RQ1, identify the long-term systemic implications and structural shifts arising from the Continental European power sector's evolution across the three modeled scenarios.

7.5.1. Key findings

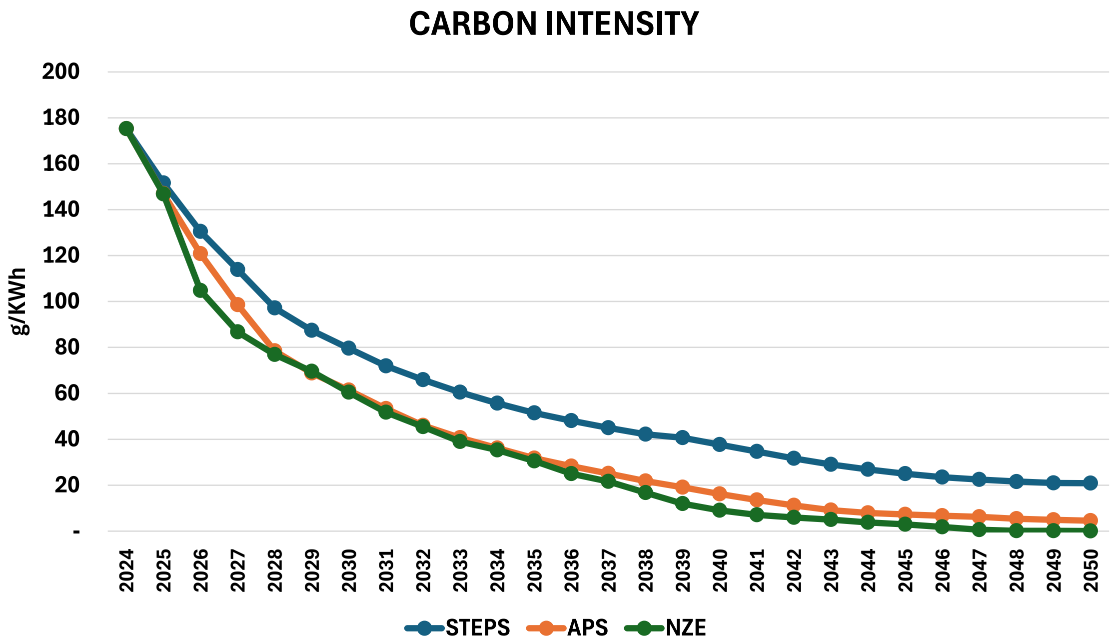

Figure 7.31: Carbon Intensity in different Scenarios

The evolution of the European electricity sector across the three analyzed scenarios (STEPS, APS, and NZE) outlines a deep structural change, transitioning from a system based on fossil fuels to a decarbonized one where technological role are radically redefined to ensure system stability and flexibility with an increasing electricity demand. Across all analyzed scenarios, the system performs a rapid and decisive phase-out of coal and oil by the early 2030s, driven by the economic pressure of an increasing Carbon Tax, stringent constraints on new installable capacity that prohibit investments in carbon-intensive sources, and a fleet approaching its end-of-life that has to be decommissioned.

Offshore wind emerges as the fundamental technology for post-2030 generation, benefiting from drastically reducing costs and capacity factors significantly higher than onshore wind, while solar PV remains a fundamental pillar in all scenarios.

The analysis highlights the model's tendency to systematically saturate the maximum installable capacity for these sources, suggesting that the limit to the transition is no longer dictated by economic viability, but rather by the European industrial system's ability to maintain extremely high production and installation rates. In this context, the challenge shifts toward the resilience of supply chains for critical raw materials (essential for panels and electronic components), the effective availability of land for such extensive infrastructure, and the necessity for enabling policies to ensure the rapid development and deployment of this massive capacity, elements that represent the true bottlenecks for the practical implementation of the modeled scenarios.

Natural gas maintains a central role in all scenarios as a direct substitute for coal and oil, revealing an intrinsic tendency of the model to invest heavily in this resource unless appropriately limited by policy constraints, as observed in the STEPS and APS scenarios. Conversely, in the NZE scenario, a high Carbon Tax and the massive investment allowed for renewables, successfully reduced its expansion too.

Carbon Capture and Storage (CCS) technologies emerge as an alternative for decarbonizing fossil-based backup. Notably, the model only begins to invest significantly in CCS once it can no longer expand conventional gas capacity due to investment limits. This effectively represents a regulatory intervention designed to force CCS deployment. Until CCS costs drop and Carbon Taxes rise further, policy frameworks remain the essential driver to overcome the cost advantages of conventional gas. This dynamic highlights that the effective industrial scale-up of emerging technologies cannot rely only on economic drivers alone but must be strategically incentivized by policy frameworks that actively facilitate their deployment to overcome the established cost advantages of conventional thermal assets.

Another fundamental result from the analysis of the scenarios is the functional shift of dispatchable technologies such as nuclear, biomass, and Gas. Marginalized in the merit order by zero-marginal-cost renewables, these sources end up providing traditional baseload power, transforming exclusively into strategic "Firm Capacity."

The reduction of their capacity factors confirms they are maintained in operation only to manage summer and winter demand peaks, driven by heating and cooling loads, when variable renewable production is also lower compared to the midseason.

While electrochemical storage is effective for managing daily (intra-day) fluctuations, particularly during the Mid-Season, when peak demand is lower and renewable generation is high, it is not yet an economically viable solution for managing extreme seasonal loads during Winter and Summer, in the absence of demand-side mitigation strategies or Long-Duration Energy Storage (LDES), the need for firm technologies remains constant. This phenomenon is particularly evident in the NZE 2050 scenario, where the model is forced to install new biomass and nuclear capacity specifically to address peak loads.

The model identifies an 'economic optimum' where it is more cost-effective to over-dimension renewable capacity and accept significant curtailment rather than investing in the prohibitive capital costs (CAPEX) required for massive, large-scale storage systems. Consequently, the system maintains a structural dependence on underutilized thermal assets, operating at low-capacity factors, to serve as Firm Capacity. These dispatchable plants are indispensable for ensuring grid reliability during the extreme demand peaks of winter and summer. A possible solution may be the use of green hydrogen: producing it via electrolysis during periods of renewable surplus and low demand (leveraging curtailment) and subsequently reconverting it into electricity via fuel cells during seasonal peaks, thereby reducing dependence on traditional dispatchable technologies to achieve total decarbonization. Another common and transversal result of all scenarios is the high reduction in the carbon intensity of the European production system, a process driven by the reduction of green technology costs, the rising Carbon Tax, and the imposition of structural constraints on conventional fossil plants. The trajectory of carbon intensity between 2024 and 2050 (Figure 7.31) shows a marked and steady decline across all scenarios, starting from a shared initial value of approximately 175 g/kWh.

During the initial decade of the simulation, all three scenarios exhibit a rapid decline in carbon intensity. However, the NZE pathway demonstrates a significantly steeper decarbonization gradient compared to the ones observed in the APS and STEPS scenarios. From 2030 onward, the trajectories diverge more sharply: while the STEPS scenario progressively slows its decrease trend, stabilizing at a residual value of approximately 20 g/kWh by 2050, the more ambitious scenarios proceed toward near-total reduction. Specifically, the APS scenario reaches a marginal threshold of approximately 5 g/kWh, while the NZE is the only scenario to reach full carbon neutrality, with a value of zero at the end of the time horizon. The overall trend of the curves describes a decarbonization process of the generation mix that becomes increasingly accelerated and deep as the level of climate ambition rises.

Additionally, the analysis of the different scenarios clearly demonstrates that the economic driver alone is insufficient to guarantee the transition within the required timeframe; market economic convenience must be associated with policy instruments that prescribe the phase-out of polluting technologies and incentivize the development of alternatives, such as battery storage, CCS and renewables. This market limitation is evident in the modeling results: without constraints on the Total Max Capacity Investment, the system would maintain a significantly higher share of natural gas production. The limitation of this source in the WEO 2024 scenarios responds not only to climate objectives but to a precise political will (particularly marked in the APS scenario) to eliminate dependence on Russian gas by 2030 and, more broadly, to reduce fossil fuel imports. The transition is thus configured not only as an environmental challenge but as a strategic objective to enhance Europe's energy independence and security.

Finally, the economic cost of each different scenario is synthesized by the Objective Value, representing the Total Discounted Cost of the system transition up to 2050:

- The STEPS scenario records the lowest value at 3,754.8 billion USD, despite maintaining high residual emissions (approx. 140 Mton of CO_2 in 2050).
- The APS scenario shows a 19.9% increase in systemic cost compared to the baseline, reaching 4,501.1 billion USD; this increase reflects the capitalization required to reduce emissions to a residue of 35 Mton.
- The NZE scenario reaches a maximum cost of 5,179.8 billion USD (+37.9% compared to STEPS), representing the most expensive but technically necessary trajectory to ensure full carbon neutrality by mid-century.

Although the NZE scenario is the costliest, it represents the economic optimum identified by the solver to eliminate fossil fuel dependence under zero-emission constraints in 2050. Moreover, the difference in the total discounted costs across the scenarios is largely driven by the different electricity demand trajectories assumed, which scale from a 2024 baseline of 3,481 TWh to 5,950 TWh in STEPS, 7,088 TWh in APS, and 7,671 TWh in NZE by 2050. This escalating demand profile, reflecting the different electrification of sectors in different scenarios, necessitates proportional increases in installed capacity and infrastructure investment, directly impacting the final Objective Value of each pathway.

8 The Horizon Effect and Salvage Value Distortions: A Comparative Analysis of 2050 and 2070 Scenarios

This chapter analyzes the horizon effect and salvage value distortions on end-of-period investments to evaluate their influence on the installation of new capacity toward the end of the simulation timeframe. Specifically, to assess these effects, the analysis focuses exclusively on the central Announced Pledges Scenario (APS), as it is the exploratory scenario most significantly affected by these distortions, as evidenced by the high concentration of onshore wind, biomass, and run-of-river installations in the final years of the original run, as evident in Table 7.5. Similar considerations can be extended to the Net Zero Emissions (NZE) scenario, although the distortions are less pronounced.

To quantify the impact of the horizon effect, a simulation extending to 2070 (the maximum period permitted by the MUIO interface) is conducted. In this run, all parameter values are held constant from 2050 to 2070 to directly isolate and evaluate salvage value distortions. Subsequently, the analysis focuses on the results up to 2050, comparing them with the outputs previously obtained in the 2050 APS simulation. This comparison is based on the Accumulated New Capacity by 2050 across all technologies, Electricity Production levels in 2050, and the resulting CO_2 Emission trajectory.

The findings reveal that the salvage value effectively incentivized capital-intensive technologies near the end of the 2050 horizon, as their high CAPEX is largely reimbursed through residual value accounting. In the short-term run, these investments served primarily to cover unmet demand peaks in a cost-efficient but opportunistic manner. Conversely, the 2070 simulation prioritizes more realistic, long-term structural solutions by internalizing costs over an extended lifecycle. While the overall variations between the two configurations are not radical, the 2070 run provides a more robust and technically representation of the energy transition's final stages.

8.1. Divergence Analysis and Mitigation of the Horizon Effect

Table 8.1: Accumulated New Capacity 2050 vs 2070 simulation

Technology	Accumulated_New_Capacity [GW] (2070 Sim.)	Accumulated_New_Capacity [GW] (2050 Sim.)	Difference % between 2070 and 2050 Sim.
BATT	350.0	335.7	4.3%
PHES	58.0	58.0	0.0%
BIO	20.2	30.9	-34.7%
GAS CCS	99.0	104.0	-4.8%
COAL	-	-	0.0%
COAL CCS	11.0	8.0	37.5%
GEO	-	-	0.0%
RESERVOIR	-	-	0.0%
ROR	0.9	7.4	-88.1%
CCGT	78.0	78.0	0.0%
SCGT	47.0	47.0	0.0%
NUC	174.4	171.9	1.4%
OIL	-	-	0.0%
PV	2,736.0	2,641.4	3.6%
WIND OFF	1,045.8	1,045.0	0.1%
WIND ON	364.3	447.0	-18.5%

Table 8.2: New Capacity 2070 simulation

New Capacity [GW] (2070 Sim.)	BATT	PHES	BIO	GAS CCS	COAL CCS	ROR	CCGT	SCGT	NUC	PV	WIND OFF	WIND ON
2024	0.7	-	-	-	-	-	-	-	-	-	-	-
2025	0.4	3.0	-	2.0	-	0.1	6.0	2.0	2.5	91.0	-	40.0
2026	2.2	3.0	-	2.0	-	0.1	6.0	2.0	3.0	110.0	-	40.0
2027	1.4	3.0	-	2.0	-	0.6	6.0	2.0	3.0	82.0	6.6	40.0
2028	2.1	3.0	-	2.0	-	-	5.0	2.0	4.0	110.0	12.7	40.0
2029	3.4	3.0	-	2.0	-	-	5.0	2.0	4.0	110.0	16.5	40.0
2030	1.2	3.0	-	2.0	-	-	5.0	2.0	5.0	110.0	30.0	40.0
2031	1.3	2.0	-	3.0	-	-	3.0	2.0	5.0	110.0	40.0	40.0
2032	3.3	2.0	-	3.0	-	-	3.0	2.0	5.0	110.0	40.0	40.0
2033	8.5	2.0	-	3.0	-	-	3.0	2.0	5.0	110.0	50.0	14.2
2034	14.5	2.0	-	3.0	-	-	3.0	2.0	5.0	110.0	50.0	-
2035	11.2	2.0	-	5.0	-	-	3.0	2.0	7.0	110.0	50.0	-
2036	11.8	2.0	-	5.0	-	-	3.0	2.0	7.0	78.2	50.0	-
2037	12.4	2.0	-	5.0	-	-	3.0	2.0	7.0	74.6	50.0	-
2038	19.2	2.0	-	5.0	-	-	3.0	2.0	7.0	104.9	50.0	-
2039	21.7	2.0	-	5.0	1.0	-	3.0	2.0	7.0	105.3	50.0	-
2040	20.6	2.0	-	5.0	1.0	-	3.0	2.0	8.0	110.0	50.0	-
2041	23.3	2.0	-	5.0	1.0	-	2.0	2.0	8.0	110.0	50.0	-
2042	22.5	2.0	-	5.0	1.0	-	2.0	2.0	8.0	110.0	50.0	-
2043	22.9	2.0	-	5.0	1.0	-	2.0	2.0	8.0	110.0	50.0	-
2044	23.4	2.0	-	5.0	1.0	-	2.0	2.0	8.0	110.0	50.0	-
2045	18.3	2.0	0.2	5.0	1.0	-	2.0	2.0	10.0	110.0	50.0	-
2046	14.4	2.0	5.0	5.0	1.0	-	1.0	1.0	10.0	110.0	50.0	-
2047	14.8	2.0	5.0	5.0	1.0	-	1.0	1.0	10.0	110.0	50.0	-
2048	18.5	2.0	5.0	5.0	1.0	-	1.0	1.0	10.0	110.0	50.0	-
2049	18.9	2.0	5.0	5.0	1.0	-	1.0	1.0	10.0	110.0	50.0	30.1
2050	37.0	2.0	-	-	-	-	1.0	1.0	7.9	110.0	50.0	-
2051	-	2.0	-	-	-	-	11.9	-	-	110.0	77.8	-
2052	7.2	2.0	-	-	-	-	3.3	-	-	110.0	4.6	-
2053	20.4	2.0	-	-	-	-	4.0	-	-	110.0	0.5	-
2054	20.4	2.0	-	-	-	-	6.7	-	-	108.1	-	-
2055	17.1	2.0	-	-	-	-	12.0	-	-	42.4	31.0	-
2056	31.7	2.0	-	-	-	-	-	-	-	110.0	28.5	-
2057	23.6	2.0	-	-	-	-	7.2	-	-	98.7	36.8	-
2058	23.3	2.0	-	-	-	-	6.2	-	-	110.0	26.7	-
2059	23.4	2.0	-	-	-	-	6.4	-	-	110.0	20.5	-
2060	18.3	2.0	-	-	-	-	7.7	-	-	110.0	25.9	-
2061	14.4	2.0	-	-	-	-	7.4	-	-	110.0	31.7	-
2062	14.8	2.0	-	-	-	-	9.7	-	-	110.0	17.4	-
2063	18.5	-	-	-	-	-	7.0	-	-	110.0	56.1	-
2064	18.9	-	-	-	-	-	8.5	-	-	110.0	46.6	-
2065	37.0	-	-	-	-	-	11.4	-	-	110.0	41.6	-
2066	-	-	-	-	-	-	8.2	-	-	66.0	61.4	-
2067	7.2	-	-	-	-	-	5.9	2.4	-	70.9	60.7	-
2068	20.4	-	-	-	-	-	2.8	5.5	-	101.3	60.7	-
2069	20.4	-	-	-	-	-	11.0	-	-	107.5	43.8	-
2070	17.1	-	-	-	-	-	7.3	2.5	-	109.5	51.4	-

The comparative analysis between the modeling horizons ending in 2050 and 2070 reveals fundamental dynamics inherent to the inter-temporal optimization logic of OSeMOSYS, especially when comparing the Accumulated New Capacity in 2050, as in Table 8.1. The overestimation of technologies such as Run-of-River (ROR) hydro and biomass in the 2050 run is primarily attributable to a distortion induced by the Salvage Value. In the presence of assets with long operational lifespans, the model perceives investments made near the end of the horizon as nearly cost-free, as the vast majority of the Capital Expenditure (CAPEX) is "refunded" to the objective function as residual value (Salvage Value) upon the simulation's closure. Extending the simulation to 2070 corrects this anomaly by forcing the algorithm to internalize long-term Operating Expenditures (OPEX) and evaluate the actual cost-effectiveness of the technology beyond the artificial 2050 threshold. Table 8.1 clearly demonstrates that in the 2070 run, the model avoids investing in biomass and run-of-river hydro by 2050. Since these technologies are no longer almost entirely offset by the salvage value, the model identifies them as being too costly for continued operation beyond the 2050 threshold.

Similarly, a shift in priorities is observed in the competition between fossil fuel technologies equipped with Carbon Capture and Storage (CCS). While the 2050 run tends to favor Gas CCS due to its lower initial investment, the 2070 horizon allows for the proper amortization of the higher CAPEX associated with Coal CCS, which emerges as the optimal choice due to its significantly lower marginal production cost. This advantage is confirmed by the economic parameters provided: despite the impact of the Carbon Tax ($200/ton) and the respective efficiency coefficients (Input Activity Ratio of 2.79 for coal and 1.91 for gas), the substantially lower fuel cost for coal ($11.67/MWh compared to $36.2/MWh for gas) results in a total variable cost of $48.93/MWh for Coal CCS, versus $78.34/MWh for Gas CCS. Over an extended timeframe, the minimization of the total discounted cost thus rewards the technology with a more capital-intensive structure but superior operational cost efficiency.

This same perfect foresight logic drives the strengthening of the Solar PV-Battery pairing and the expansion of nuclear power, as evident in Table 8.1. With a 45-year horizon, the model recognizes that the cumulative savings generated by technologies with near-zero marginal costs far outweigh the initial burden of capacity and storage investments. In this context, Offshore Wind consolidates its role as a strategic pillar for post-2050 production. Conversely, Onshore Wind is penalized in the 2070 simulation. In the 2050 run, the model tended to invest heavily in onshore capacity during the final years of the simulation specifically to cover demand peaks, exploiting the fact that a large portion of the CAPEX would be offset by the salvage value. By extending the horizon, onshore wind is progressively replaced by offshore capacity (as evident in Table 8.2), which is deemed more efficient for the future energy mix. Finally, Nuclear energy also benefits from the temporal extension; its high CAPEX, invested in the early years to capitalize on low marginal costs, finds the necessary timeframe in a long-term horizon for complete and effective economic saturation of the asset.

8.2. Long-term Horizon Impact on the 2050 Production Mix

Table 8.3: 2050 Total Net Electricity Production: 2050 vs 2070 simulation

Technology	2050 Elec. Production [TWh] (2070 Sim.)	2050 Elec. Production [TWh] (2050 Sim.)	Difference % between 2070 and 2050 Sim.
BATT	459.9	434.4	5.9%
PHES	94.2	88.5	6.5%
BIO	50.6	50.6	0.0%
GAS CCS	238.5	230.5	3.5%
COAL	-	-	0.0%
COAL CCS	42.3	30.8	37.5%
GEO	23.2	23.3	-0.4%
RESERVOIR	363.0	363.0	0.0%
ROR	281.6	286.1	-1.5%
CCGT	72.1	63.8	13.0%
SCGT	25.2	17.1	47.5%
NUC	876.9	862.5	1.7%
OIL	0.2	0.1	196.8%
PV	2,874.9	2,685.2	7.1%
WIND OFF	2,538.8	2,735.6	-7.2%
WIND ON	503.5	537.4	-6.3%

The extension of the modelling horizon to 2070 induces a profound reconfiguration of the 2050 production mix (Table 8.3), favouring assets with cost structures optimized for long-term operation and superior operational cost efficiency. Coal CCS emerges as a cornerstone of the baseload generation, with a production increase of 37.5% (rising from 30.8 to 42.3 TWh). This shift occurs because a generation cost of $48.93/MWh renders Coal CCS substantially more competitive than Gas CCS (which remains stagnant at +3.5%) once high capital expenditures are amortized over a 45-year timeframe. Concurrently, a marked prevalence of solar photovoltaics (PV) is observed, with production growing by 7.1% (reaching 2,874.9 TWh) at the expense of wind power; specifically, Offshore and Onshore wind production decrease by 7.2% and 6.3%, respectively.

This dynamic is driven by the exceptionally low CAPEX of PV and the optimization logic of OSeMOSYS, which seeks to saturate renewable capacity with the most cost-effective zero-marginal-cost technology. Consequently, offshore wind is relegated to a "middle-ground" status, as it proves costlier than solar and lacks the "firmness" or dispatchability provided by Coal CCS.

The shift toward a PV-dominant mix imposes greater flexibility and stability requirements on the grid, which the model addresses by intensifying the utilization of peaking technologies and storage assets. Production from Simple Cycle Gas Turbines (SCGT) increases by 47.5%, complemented by a 13% rise in Combined Cycle Gas Turbine (CCGT) output. Simultaneously, the discharge from batteries (BATT +5.9%) and pumped hydro (PHES +6.5%) is dispatched with higher granularity to manage diurnal load cycles. In conclusion, extending the simulation horizon to 2070 mitigates the distortions inherent in short-term scenarios, delineating an energy architecture founded on the complementarity between a Coal CCS thermal baseload and a predominant solar PV share. The inherent intermittency of the latter is effectively balanced through the systematic and optimized deployment of diversified flexibility and storage resources.

8.3. Impact of Extended Foresight on CO_2 Trajectories

Table 8.4: Total CO_2 Emission Trajectories: 2050 vs 2070 simulation

Year	Total CO2 Emission (2070 Sim.) [Mton]	Total CO2 Emission (2050 Sim.) [Mton]	Difference % 2070 and 2050 Sim.
2024	675.60	675.60	0.0%
2025	583.75	587.32	-0.6%
2026	497.65	501.34	-0.7%
2027	421.45	424.65	-0.8%
2028	347.91	351.08	-0.9%
2029	315.85	319.08	-1.0%
2030	290.26	293.87	-1.2%
2031	260.11	263.49	-1.3%
2032	231.35	234.63	-1.4%
2033	209.28	213.81	-2.1%
2034	191.83	195.79	-2.0%
2035	173.00	176.86	-2.2%
2036	158.44	161.67	-2.0%
2037	144.99	147.68	-1.8%
2038	129.06	131.27	-1.7%
2039	113.33	118.10	-4.0%
2040	97.32	102.59	-5.1%
2041	82.41	87.69	-6.0%
2042	68.12	74.40	-8.4%
2043	56.20	62.20	-9.6%
2044	52.10	55.18	-5.6%
2045	49.38	51.78	-4.6%
2046	46.31	48.65	-4.8%
2047	44.05	46.33	-4.9%
2048	42.44	41.08	3.3%
2049	41.27	37.68	9.5%
2050	43.45	35.85	21.2%

The comparative analysis of CO_2 emission trajectories (Table 8.4) and electricity production patterns (Table 8.3) reveals a strategic divergence driven by the Horizon Effect, where the 2070 simulation adopts a more proactive decarbonization pathway in the early-to-midterm, achieving emission levels up to 9.6% lower than the 2050 run by 2043. This trend indicates that with extended foresight, the model finds it economically optimal to accelerate the deployment of high-CAPEX, zero-marginal-cost assets early on to maximize long-term savings. However, a notable reversal occurs at the end of the short-term horizon, with 2070 simulation emissions reaching 43.45 Mt in 2050, a 21.2% increase compared to the 35.85 Mt of the 2050-only run. This divergence is rooted in a structural rationalization of the technology mix: the 2070 horizon prioritizes a 37.5% increase in Coal CCS production (42.3 TWh vs 30.8 TWh) and a 47.5% surge in Simple Cycle Gas Turbine (SCGT) generation (25.2 TWh vs 17.1 TWh) to provide the necessary firm capacity and flexibility for a grid with higher Solar PV penetration (+7.1%).

While the 2050-only run achieves lower localized emissions by exploiting the Salvage Value of ‘stop-gap’ renewable measures like offshore wind, the 2070 simulation accepts higher residual emissions in 2050 as part of a more resilient and cost-effective industrial strategy designed to sustain decarbonization efforts through the following decades.

8.4. Conclusion

In conclusion, the comparative analysis between the 2050 and 2070 horizons demonstrates that salvage value distortions and the end-horizon effect significantly skew investment decisions in short-term simulations. The 2050-only run exhibited a clear "accounting bias," where the model favored capital-intensive technologies like Run-of-River hydro, biomass, and onshore wind in the final years simply because their high CAPEX is virtually reimbursed through residual value accounting. These investments served as opportunistic "stop-gap" measures to cover unmet demand peaks rather than representing a sustainable industrial strategy.

Conversely, the 2070 simulation corrected this "myopia" by forcing the model to internalize long-term operating costs and evaluate the actual lifecycle efficiency of the assets. This resulted in a more robust and realistic energy mix centered on the complementarity of Coal CCS, which becomes economically saturated over the extended period, and a dominant Solar PV-Battery architecture.

Ultimately, the lower emission profile observed in the 2050-only run represents a localized optimization constrained by a fixed end-date, rather than a globally efficient decarbonization strategy. The 2070 simulation provides a more robust systemic framework, highlighting that a viable energy transition depends on prioritizing technologies with low marginal costs and long-term operational stability. This shift demonstrates that the pursuit of immediate, short-term targets can inadvertently overlook the total lifecycle efficiency and structural resilience required for a sustainable long-term energy architecture.

9 Conclusions and Future Research

9.1. Summary of Findings

The analyses conducted in this thesis confirm that long-term energy-system projections are strongly shaped by model structure, methodological assumptions, and input data choices. Model complexity alone does not guarantee reliable trajectories; rather, the coherence of assumptions and the way policy and feasibility constraints are represented critically influence outputs. This conclusion is consistent with the retrospective evidence developed in Chapter 1: the comparison between WEO 2010 projections, historical time series (1990–2024), and WEO 2024 pathways shows that WEO 2010 significantly underestimated wind and solar deployment, especially PV, while implying a more persistent global dependence on fossil fuels. The thesis interprets this divergence as largely driven by conservative assumptions on renewables' learning and cost reductions and by the simulation-based nature of the WEO modelling framework. This evidence also shows that greater model complexity does not automatically translate into more accurate projections. Even highly sophisticated frameworks can produce misleading trajectories when key assumptions and inputs, such as technology learning rates, cost reductions and the representation of policy and feasibility constraints, are conservative, outdated, or incomplete.

Building on this premise, the thesis developed a simplified, aggregated, single-region least-cost model for Continental Europe in OSeMOSYS (implemented through MUIO), supported by a newly constructed aggregated dataset and a calibrated 2024 baseline consistent with an empirically reconstructed Reference Energy System (RES). The model was then used to address two research questions: whether a simplified cost-minimizing optimizer can reproduce WEO 2024 system-level trends under harmonized inputs (RQ1), and what transition insights emerge for the European power sector up to 2050 across alternative pathways (RQ2). In addition, the thesis explicitly investigated end-of-horizon effects horizon effects and salvage value distortions to assess the robustness of 2050 insights and to strengthen the interpretation of long-horizon optimization results.

Findings for RQ1: Benchmarking a simplified OSeMOSYS model against WEO 2024

To answer RQ1, the thesis performed a structured benchmarking exercise comparing OSeMOSYS outputs with WEO 2024 results for Continental Europe. Owing to data-availability constraints, the comparison was limited to STEPS and APS, and it focused on indicators that can be compared like-for-like across frameworks, most notably electricity generation by source, while excluding a direct CO_2 benchmarking because WEO regional emissions are not reported exclusively for the power sector. Prior to comparison, datasets were harmonized by converting OSeMOSYS outputs from net to gross electricity, ensuring consistency with WEO reporting conventions.

Overall, the benchmarking shows that, despite its simplified structure, OSeMOSYS captures the aggregate 2050 outcome for Continental Europe with high robustness, especially once results are grouped into macro-categories. In STEPS, OSeMOSYS underestimates total generation by about 3% (2030), 8% (2035), and 4% (2050); however, by 2050 it reproduces the macro split with high accuracy, underestimating fossil-based generation by only ~1.5% and renewable/zero-carbon generation by ~4%. In APS, total generation is similarly underestimated by about 3% (2030), 7% (2035), and 3% (2050); yet, when aggregated into Fossil vs. Renewable/Zero-carbon categories, alignment improves markedly: by 2050, OSeMOSYS underestimates fossil generation by ~3.8% and renewable/zero-carbon generation by ~2%.

At the same time, the model exhibits non-negligible divergences along intermediate trajectories and at the level of single technologies. These divergence patterns are consistent with identifiable structural differences between the two frameworks. OSeMOSYS is a deterministic least-cost optimization model with perfect foresight, whereas WEO 2024 pathways are generated within a simulation-based, policy-driven framework that embeds feasibility constraints, institutional inertia and political preferences. Accordingly, WEO trajectories reflect more incremental, year-anchored dynamics and technology adoption behavior, while OSeMOSYS computes an intertemporal least-cost solution conditional on the constraints imposed. Technology allocation mechanisms also differ: linear programming in OSeMOSYS tends toward more polarized "corner" solutions, whereas WEO commonly relies on adoption and market-share formulations, such as Logit and Weibull functions, that yield smoother and more diversified mixes. Additional drivers include the single-region geographic aggregation, simplified operational representation (notably the absence of unit commitment and detailed ramping/start-up constraints, which reduces system "friction"), and differences in data depth, with WEO drawing on extensive proprietary datasets and forecasting tools while this study relies on publicly available sources. Taken together, these factors help explain why system-wide 2050 outcomes align more closely than the 2030–2040 trajectories and technology-level splits.

Findings for RQ2: key transition trends for Continental Europe to 2050

To answer RQ2, the thesis analyses three pathways aligned with WEO 2024 narratives, Stated Policies Scenario (STEPS), Announced Pledges Scenario (APS), and an NZE-consistent pathway, within a purely economic, least-cost optimization framework. The model is configured to mirror WEO 2024 scenario logic: scenario differentiation is implemented primarily through electricity demand trajectories, evolving technology cost and performance assumptions, fuel prices, and carbon pricing, as well as, under the normative pathway, explicit emissions constraints. Consistent with increasing climate ambition from STEPS to APS and NZE, carbon prices rise while the costs of low-carbon technologies decline, strengthening the relative competitiveness of renewables and other clean options. Across scenarios, the set of available technologies is kept constant; what changes are deployment and transition constraints, including maximum annual investment levels and bounds on year-to-year changes in electricity production. As emphasized in the thesis, a cost-minimization framework does not automatically reproduce the policy-driven and feasibility constraints embedded in institutional scenarios; scenario-specific bounds are therefore introduced to partially approximate deployment realism and transition pacing consistent with WEO 2024 narratives.

Across scenarios, the model produces progressively deeper decarbonization as ambition increases, with a growing dominance of renewables and an evolving role for firm capacity. Total discounted system cost rises with ambition: STEPS is least costly at 3,754.8 billion USD, APS increases to 4,501.1 billion USD (+19.9% vs STEPS), and NZE reaches 5,179.8 billion USD (+37.9% vs STEPS), reflecting the scale of investment required to achieve near-zero or zero emissions by mid-century. A major driver of these differences is the assumed electrification intensity and therefore electricity demand growth, which rises from 3,481 TWh (2024) to 5,950 TWh (STEPS), 7,088 TWh (APS), and 7,671 TWh (NZE) by 2050.

In emissions terms, the scenarios reach distinct end-states by 2050: STEPS retains high residual emissions (≈ 140 Mt CO_2 in 2050), APS reduces emissions to a low residual level (≈ 35 Mt CO_2 in 2050), while NZE achieves full carbon neutrality by 2049–2050 under the imposed zero-emission requirement. Within NZE, a notable result is the emergence of a strongly non-linear decarbonization profile: although a linear emissions trajectory is imposed as a constraint, the endogenous solution produces an almost exponential decline driven by interacting effects, rising carbon taxation, declining renewable CAPEX, retirement of the existing fleet, and constrained fossil deployment, leading to earlier abatement than the minimum required path.

A recurring insight across scenarios is that economic signals alone are insufficient to deliver the full transition pace implied by high-ambition pathways. Even with falling renewable costs and increasing carbon prices, deep decarbonization requires complementary policy and feasibility mechanisms that accelerate fossil phase-out, support less immediately competitive technologies, and enforce constraints consistent with energy-security objectives. As VRE shares rise, dispatchable conventional technologies shift structurally from bulk supply toward peaking and firm-capacity roles, with declining capacity factors. Completing the fossil phase-out becomes increasingly dependent on system flexibility, especially demand-side flexibility and long-duration energy storage (LDES), to shift electricity from periods of renewable surplus (curtailment) to periods of low renewable availability and higher demand.

Horizon effects and salvage value distortions

To strengthen the robustness of long-horizon results, the thesis explicitly investigates a classic optimization bias: the horizon effect and the role of salvage value in distorting end-of-period investment incentives. Focusing on APS Scenario, the 2050-limited run exhibits concentrated on late additions (e.g., onshore wind, biomass, run-of-river) that appear opportunistic rather than structurally driven, consistent with an end-year bias. To isolate this effect, the model is re-run with an extended horizon to 2070, keeping parameter values constant beyond 2050, and outcomes up to 2050 are compared across the two horizons. The longer horizon reshapes technology competition by allowing high-CAPEX options to amortize over a longer period: in particular, the 2050 horizon tends to favor Gas CCS due to lower upfront costs, whereas the 2070 horizon increases the competitiveness of Coal CCS because its lower variable costs become more valuable over multiple decades. The extended horizon also strengthens investments in high-CAPEX, near-zero marginal cost technologies and complements, most notably the PV–battery pairing and nuclear, since their cumulative savings increase over a longer evaluation window. As a result, the 2050 production mix shifts materially under the 2070 horizon: Coal CCS increases (+37.5%), solar PV rises (+7.1%), while onshore and offshore wind decline (about −6% to −7%). The PV-dominant configuration increases flexibility requirements, which the model meets through higher peaking generation and storage dispatch, including increased output from SCGT (+47.5%), CCGT (+13%), and greater use of batteries and pumped hydro (about +6%). In emissions terms, extended foresight accelerates decarbonization in the early-to-mid term (up to −9.6% emissions by 2043 relative to the 2050 run) but yields higher residual emissions in 2050 (43.45 Mt vs 35.85 Mt), reflecting a least-cost trade-off between firm adequacy and marginal emissions under a more PV- and CCS-intensive architecture. Overall, the analysis shows that horizon length and terminal-year treatment can materially affect “2050” outcomes, and that extended-horizon checks are essential to interpret end-state results from long-term optimization models.

Concluding synthesis and contribution of the thesis

Overall, the thesis provides evidence that open-source, simplified, aggregated least-cost models can generate robust system-wide end-state insights for energy planning, particularly when interpreted at an aggregated macro level. At the same time, it clarifies where simplified optimization is structurally limited (technology-level pathways, intermediate milestones, and policy feasibility dimensions) and demonstrates how modelling choices, temporal resolution, geographical aggregation, modelling horizon, and the absence of unit commitment and sector coupling materially influence outcomes.

Beyond the scenario findings, the thesis provides four original contributions: (i) a structured benchmarking between a simplified, aggregated OSeMOSYS model and WEO 2024 for Continental Europe, clarifying when simplified models can still provide robust insights and where divergences should be expected; (ii) the implementation and documentation of a reproducible modelling chain using MUIO, providing a reference setup; (iii) the construction of a new simplified, aggregated dataset for the Continental European power sector, structured for implementation in OSeMOSYS through the MUIO interface; and (iv) the synthesis of system-level trends for the Continental European power sector under increasing climate ambition, complemented by an explicit assessment of end-of-horizon distortions and their implications for interpreting 2050 outcomes.

9.2. Limitations of the Study & Directions for Future Research

This section outlines the primary limitations inherent in the long-term optimization of the Continental European power system through 2050. It focuses on the constraints arising from the simplified, aggregated modelling approach necessitated by the benchmarking exercise against WEO 2024 and the requirements of RQ1. Furthermore, it identifies potential methodological improvements and provides a series of recommendations for future research aimed at refining the optimization of the European electricity sector.

9.2.1. Limitations of the Study

The following section details the primary limitations related specifically to the analysis conducted on the optimization of the European electricity sector by 2050. These involve the intrinsic characteristics of the model, the methodological assumptions, and the modelling choices that dictated a decisive impact on the outputs, thereby influencing the trajectory of each scenario.

Methodological and Technical Limitations:

- Model Technical Constraints: The absence of ramping constraints and start-up/shut-down costs led the model to interpret technologies as being extremely flexible, resulting in oscillatory production behaviours that do not always reflect the actual operational reality of the plants, especially evident when analysing the production by time slices. Furthermore, the lack of a minimum production constraint [Minimum Stable Level] also impacted the generation outputs. The implementation of ramping constraints and minimum stable levels prevents unrealistic intermittent operation and seasonal-only dispatch of power plants. Preliminary analysis of generation profiles across different time slices revealed that many conventional dispatchable technologies, such as nuclear, biomass, and gas-fired units, were only activated during the winter and summer seasons to meet peak demand, remaining entirely offline during the mid-seasons. By incorporating these technical constraints, the model avoids frequent startup and shutdown cycles, ensuring that these plants maintain a more continuous and technically feasible operation profile. This approach better reflects the operational reality of baseload and continuous thermal units, which are characterized by high startup costs and physical limitations on power fluctuations.

- Temporal Resolution: The modelling choice of not implementing a continuous hourly resolution (8,760 hours) penalized storage technologies in favour of firm capacity technologies.
- Isolated Electricity Sector: The choice to model the electricity sector exclusively, without integrating the thermal sector, penalized technologies such as biomass, whose production and cost-effectiveness are intrinsically based on cogeneration.
- Linear Projections of Costs and Demand: A structural limitation of the modelling lies in the assumption of linear evolution trajectories for key macroeconomic and technological variables. The model assumes that the decline in technology CAPEX (such as photovoltaics or storage) follows a linear trend. Technological learning curves often follows "S-curves." Similarly, the assumption of steady electricity demand growth until 2050 (from the initial 3,481 TWh to 7,671 TWh in the NZE) does not account for economic cycles, geopolitical shocks, or potential sudden accelerations in the rate of industrial and civil electrification, which can make the transition much more turbulent than predicted by a gradual linear progression assumed.
- Invariance of Load Profiles: A further simplification and limitation involve the assumption that load profiles remain constant over time, without evaluating how potential variations in consumption patterns might influence the mix, as well as the impact of demand side mitigation.

- Technological Aggregation: A further limitation of this study lies in the decision to aggregate diverse plant configurations into single reference technologies for the entire European region. This simplification prevents the model from capturing the technical heterogeneities and efficiency variations specific to local contexts, relying instead on average performance parameters that may not fully reflect the unique technological barriers or opportunities within individual Member States.

Geographical and External Constraints:

- Geographical Simplification: A significant methodological limitation is the Copperplate hypothesis, which treats Europe as a single electrical node without bottlenecks, assuming that grid capacity is sufficient to manage all loads.
- Grid Congestion: In reality, the physical limits of national and cross-border transmission grids restrict energy transfer (for example, from offshore wind in the North to load centers in the South), suggesting that actual curtailment could be significantly higher than modeled.
- Regional Heterogeneity: The decision to model the study area as a single aggregated entity, rather than subdividing it into distinct regions with localized demand profiles and technological mixes, limited the model's spatial granularity. Consequently, the resulting outputs are less reflective of the specific socio-economic and technical conditions found across different European contexts.
- Supply Chain and Raw Materials: Physical limits of global supply chains (scarcity of lithium, copper, or rare earths) are not considered. Such constraints can cause shocks in CAPEX prices, potentially making ambitious scenarios like Net Zero (NZE) significantly more costly than predicted.
- Climate Feedback: The model considers natural resources (wind, sun, water) as constant; however, climate change is already altering hydroelectric yield and solar panel efficiency, while simultaneously modifying seasonal demand profiles.

Economic and Dynamic Modeling Constraints:

- Discount Rate: The use of a single social discount rate (e.g., 5%) does not reflect the diverse financial risk profiles associated with different technologies.
- Demand Elasticity: The price elasticity of demand is not considered; in reality, an increase in system costs can induce a contraction in consumption or a more pronounced demand-side response.

- Dynamic Stability: The absence of modeling for ancillary services and grid inertia represents a technical gap, as an inverter-based system requires additional investments for frequency stability that the model does not quantify.
- Inter-annual Variability: The use of a single meteorological year (2023 for defining renewable capacity factors) does not account for variability between different years (e.g., dry years or years with low wind speeds), which would necessitate more extensive strategic reserves.
- Endogenous Technological Learning (Learning Curves): The model assumed exogenous cost reduction curves for technologies, implying that cost reductions occur independently of the capacity the model decides to install. Costs decrease because of installation (economies of scale). Not modeling this feedback (endogenous learning) can lead to an underestimation of the transition speed or an overestimation of final system costs.
- Exogenous Fuel Price Trajectories: Similarly, the model treats fuel prices as exogenous inputs based on predefined trajectories, assuming that price evolutions occur independently of the fuel volumes consumed within the simulation. Large-scale shifts in energy demand, such as a rapid phase-out of fossil fuels or a massive surge in hydrogen consumption, would trigger significant market responses, influencing prices through supply and demand dynamics. By not modelling this endogenous feedback (where the model’s own choices affect fuel costs), the analysis may fail to capture potential 'price-dampening' effects in declining sectors or 'price-spikes' in rapidly growing markets

In summary, the primary model-related and methodological limitations have been analysed.

9.2.2. Directions for Future Research

Transitioning to Open-Source and Code Customization

A natural progression of this thesis should start directly from the critical analysis of the results obtained and the limitations identified, aiming to overcome them. Specifically, a potential pathway for continuing this study would first involve transitioning to the open-source version of OSeMOSYS, moving beyond the use of the MUIO user interface. This shift would allow for direct modification of the model's source code (the .txt file in GNU MathProg) to implement ramping constraints, thereby introducing a percentage-based relationship for production between different time slices. This would prevent the sharp discontinuities observed in the production outputs and favour a more continuous generation profile.

Operational Flexibility: Implementing Ramping Constraints

To implement this constraint, new parameters and equations must be declared within the model file. First, it is necessary to define parameters that determine how quickly a technology can vary its output, typically expressed as a fraction of the total capacity per unit of time:

- RampingUpLimit(r, t): The maximum allowable increase in production, usually expressed as a fraction of total capacity (e.g., 0.20 for 20% of capacity per hour).
- RampingDownLimit(r, t): The maximum allowable reduction in production.

Furthermore, a new parameter, such as NextTimeSlice(l), must be defined to map the successor for each time slice l. This allows the model to recognize the sequential succession of time slices, a characteristic that is otherwise lost in the standard simultaneous optimization of the base version.

Subsequently, the constraint is implemented in terms of the RateOfActivity. A possible logical formulation for the ramp-up constraint is:

$$\forall_{r,l,t,y}\ \mathrm{RateOfActivity}_{r,\mathrm{NextTimeSlice}(l),t,y} - \mathrm{RateOfActivity}_{r,l,t,y} \leq \mathrm{RampingUpLimit}_{r,t,y} * \mathrm{TotalCapacityAnnual}_{r,t,y} * \mathrm{CapacityToActivityUnit}_{r,t}$$

Similarly, for the ramp-down constraint:

$$\forall_{r,l,t,y}\ \mathrm{RateOfActivity}_{r,l,t,y} - \mathrm{RateOfActivity}_{r,\mathrm{NextTimeSlice}(l),t,y} \leq \mathrm{RampingDownLimit}_{r,t,y} * \mathrm{TotalCapacityAnnual}_{r,t,y} * \mathrm{CapacityToActivityUnit}_{r,t}$$

Stability Constraints: Minimum Stable Operating Levels

Another technical option to favour more continuous solutions and simulate the complexity of real-world dispatch is the implementation of a constraint requiring each technology to always produce at least a certain share of its installed capacity.

To implement this, the new parameter MinStableLevel(r, t, y) must be defined, indicating the minimum load fraction (e.g., 0.3 for 30%). The logical formulation of the constraint in terms of RateOfActivity would be:

$$\forall_{r,l,t,y}\ \mathrm{RateOfActivity}_{r,l,t,y} \geq \mathrm{MinStableLevel}_{r,t,y} * \mathrm{TotalCapacityAnnual}_{r,t,y} * \mathrm{CapacityToActivityUnit}_{r,t}$$

Enhancing Spatial Resolution: Regional Disaggregation

Another modification for future research involves modelling additional regions to represent continental Europe divided into Southern, Northern, Western, and

Eastern Europe, or by individual countries/clusters. This would allow for the representation of different load and demand profiles, specific weather characteristics influencing renewable production and Capacity Factors (CF), resulting in production mixes that are more heterogeneous and aligned with local specificities.

Temporal Resolution and Storage Optimization

Furthermore, it is essential to increase the temporal resolution to hourly (8,760 hours) to avoid penalizing storage. This would allow, also, for a more accurate modulation and representation of renewable variability, capturing the behaviour of renewable CFs with much higher granularity. The transition to an hourly resolution is particularly necessary if ramping constraints are introduced, as they would then become effectively binding.

New Vectors and Technologies: The Hydrogen Economy

Regarding technologies, electrolyzers and fuel cells would be introduced, alongside green hydrogen as a new commodity to enhance yearly storage capabilities.

Sectoral Coupling: Integration of the Thermal Sector

Additionally, the thermal sector would be integrated by disaggregating thermal demand into:

- Residential and Commercial Thermal Demand (Buildings): Linked to human comfort and basic services.
  - Space Heating: Seasonal demand (high in winter, zero in summer) at low temperatures (35-70°C).
  - Domestic Hot Water: Constant demand throughout the year at approximately 60°C.
- Industrial Thermal Demand (Process Heat):
  - Low Temperature (<100-150°C): Food, textile, and industrial laundry industries. Easily electrifiable with industrial heat pumps.
  - Medium Temperature (150-400°C): Chemical, paper, and plastic industries. Requires electric boilers, biomass, or concentrated solar thermal.
  - High Temperature (>400°C): Steel, cement, and glass (hard-to-abate sectors). Heat is often provided by green hydrogen or direct combustion of biomass/gas with CCS.

Thermal modelling would necessitate the inclusion of the following technologies:

- Residential and Commercial Sector: Electric boilers and heat pumps.
- Industrial Sector: Combined Heat and Power (CHP) and industrial heat pumps.
- Thermal Energy Storage (TES):
    - Daily TES: Large, insulated water tanks that accumulate heat during the day to release it at night.
    - Seasonal TES (PTES - Pit Thermal Energy Storage): Massive underground basins that store excess summer heat for use in mid-winter.

Strategic Assessment: Future Sensitivity Analyses

Finally, another potential direction for future research involves conducting a series of sensitivity analyses. By varying the following input parameters, it would be possible to comprehensively assess the extent of their impact on the model's outputs and strategic choices:

- Discount rate,
- Different CAPEX cost projections for green technologies,
- Alternative fuel cost projections for both fossil fuels and biomass,
- Differentiated deployment rates and maximum capacity investment limits for various technologies.

Anticipated Outcomes on System Dynamics

From these initial modifications, the expected results include more gradual and less discontinuous production profiles, as well as a significant expansion of energy storage.

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A Appendix A

The appendix presents the main algebraic formulations of OSeMSOSYS.

A.1. OSeMOSYS Algebraic Formulation

Objective Function:

minimize $\sum_{y,r} \text{TotalDiscountedCost}_{y,r}$

Total Discounted Cost:

$\forall_{y,t,r} \text{TotalDiscountedCostByTechnology}_{y,t,r} = \text{DiscountedOperatingCost}_{y,t,r} + \text{DiscountedCapitalInvestment}_{y,t,r} + \text{DiscountedTechnologyEmissionPenalty}_{y,t,r} - \text{DiscountedSalvageValue}_{y,t,r}$

$\forall_{r,y} \text{TotalDiscountedCost}_{r,y} = \sum_t \text{TotalDiscountedCostByTechnology}_{r,t,y} + \sum_s \text{TotalDiscountedStorageCost}_{r,s,y}$

Operating Cost:

$\forall_{y,l,t,r} \text{VariableOperatingCost}_{y,l,t,r} = \sum_m \text{RateOfActivity}_{y,l,t,m,r} * \text{VariableCost}_{y,t,m,r}$

$\forall_{y,t,r}\ \text{AnnualVariableOperatingCost}_{y,t,r} = \sum_l \text{VariableOperatingCost}_{y,l,t,r}$

$\forall_{y,t,r}\ \text{AnnualFixedOperatingCost}_{y,t,r} = \text{TotalCapacityAnnual}_{y,t,r} * \text{FixedCost}_{y,t,r}$

$\forall_{y,t,r} \text{OperatingCost}_{y,t,r} = \text{AnnualFixedOperatingCost}_{y,t,r} + \text{AnnualVariableOperatingCost}_{y,t,r}$

$\forall_{r,t,y}\ \text{DiscountedOperatingCost}_{r,t,y} = \frac{\text{OperatingCost}_{r,t,y}}{(1+\text{DiscountRate}_{r,t})^{(y-\text{StartYear}+0.5)}}$

Capital Cost:

$\forall_{y,t,r} \text{CapitalInvestement}_{y,t,r} = \text{CapitalCost}_{y,t,r} * \text{NewCapacity}_{y,t,r}$

$\forall_{y,t,r} \text{DiscountedCapitalInvestment}_{y,t,r} = \frac{\text{CapitalInvestment}_{y,t,r}}{((1+\text{DiscountRate}_{t,r})^{(y-\text{StartYear})})}$

Salvage Value:

$\forall_{t,r,y:(y+\text{OperationalLife},r)<\text{StartYear}+\text{card(Year)}} \text{SalvageValue}_{y,t,r} = 0$

$\forall_{t,r,y:(y+\text{OperationalLife},r)\geq\text{StartYear}+\text{card(Year)}} \text{SalvageValue}_{y,t,r} = \text{NewCapacity}_{y,t,r} * \text{CapitalCost}_{y,t,r} * [\frac{1-\left(\left(1+\text{DiscountRate}_{t,r}\right)^{(\text{StartYear}+\text{card(Year)}-y)}-1\right)}{\left(1+\text{DiscountRate}_{t,r}\right)^{(OperationalLife_{t,r})}-1}] \rightarrow$ *Sinking Fund Depreciation*

$\forall_{t,r,y:(y+\text{OperationalLife},r)\geq \text{StartYear}+\text{card(Year)}} \text{SalvageValue}_{y,t,r} = \text{NewCapacity}_{y,t,r} * \text{CapitalCost}_{y,t,r} * [1 - \frac{StartYear+card(Year)-y}{OperationalLife_{r,t}}]$ → *Linear Depreciation*

$\forall_{y,t,r} \text{DiscountedSalvageValue}_{y,t,r} = \frac{\text{SalvageValue}_{y,t,r}}{(1+\text{DiscountRate}_{r,t})^{\text{card(YEAR)}}}$

Storage:

$\forall_{y,t,r} \text{StorageCharge}_{s,y,l,r} = \sum_{t,m} \text{RateOfActivity}_{y,l,t,m,r} * \text{TechnologyToStorage}_{t,m,s,r} * \text{YearSplit}_{y,l}$

$\forall_{y,t,r} \text{StorageDischarge}_{s,y,l,r} = \sum_{t,m} \text{RateOfActivity}_{y,l,t,m,r} * \text{TechnologyFromStorage}_{t,m,s,r} * \text{YearSplit}_{y,l}$

$\forall_{s,y,l,r} \text{NetStorageCharge}_{s,y,l,r} = \text{StorageCharge}_{s,y,l,r} - \text{StorageDischarge}_{s,y,l,r}$

$\forall_{b,s,r} \text{StorageLevel}_{b,s,r} = \sum_{l,y} \frac{\text{NetStorageCharge}_{s,y,l,r}}{\text{YearSplit}_{y,l}} * \text{StorageInflectionTimes}_{y,l,b}$

$\forall_{r,s,y} \text{StorageUpperLimit}_{r,s,y} = \text{AccumulatedNewStorageCapacity}_{r,s,y} + \text{ResidualStorageCapacity}_{r,s,y}$

$\forall_{r,s,y} \text{StorageLowerLimit}_{s,r} = \text{MinStorageCharge}_{r,s,y} * \text{StorageUpperLimit}_{r,s,y}$

$\forall_{b,s,r} \text{StorageLowerLimit}_{s,r} \leq \text{StorageLevel}_{b,s,r} \geq \text{StorageUpperLimit}_{s,r}$

$\forall_{r,s,y} \text{CapitalInvestmentStorage}_{r,s,y} = \text{CapitalCostStorage}_{r,s,y} * \text{NewStorageCapacity}_{r,s,y}$

$\forall_{y,s,r} \text{DiscountedCapitalInvestmentStorage}_{y,s,r} = \frac{\text{CapitalInvestmentStorage}_{y,s,r}}{((1+\text{DiscountRate}_{r})^{(y-\text{StartYear})})}$

$\forall_{s,r,y:(y+\text{OperationalLifeStorage},r)<\text{StartYear}+\text{card(Year)}} \text{SalvageValueStorage}_{y,s,r} = 0$

$\forall_{s,r,y:(y+\text{OperationalLifeStorage},r)\geq \text{StartYear}+\text{card(Year)}} \text{SalvageValueStorage}_{y,s,r} = \text{CapitalInvestmentStorage}_{y,s,r} * [\frac{1-((1+\text{DiscountRate}_{r})^{(\text{StartYear}+\text{card(Year)}-y)}-1)}{(1+\text{DiscountRate}_{r})^{(OperationalLifeStorage_{s,r})}-1}]$ → *Sinking Fund Depreciation*

$\forall_{s,r,y:(y+\text{OperationalLifeStorage},r)\geq \text{StartYear}+\text{card(Year)}} \text{SalvageValueStorage}_{y,s,r} = \text{CapitalInvestmentStorage}_{y,s,r} * [1 - \frac{StartYear+card(Year)-y}{OperationalLifeStorage_{r,s}}]$ → *Linear Depreciation*

$\forall_{y,s,r} \text{DiscountedSalvageValueStorage}_{y,t,r} = \frac{\text{SalvageValueStorage}_{y,s,r}}{(1+\text{DiscountRate}_{r})^{\text{card(YEAR)}}}$

$\forall_{r,s,y} \text{TotalDiscountedStorageCost}_{r,s,y} = \text{DiscountedCapitalInvestmentStorage}_{r,s,y} - \text{DiscountedSalvageValueStorage}_{r,s,y}$

Demand:

$\forall_{r,l,f,y} \text{RateOfDemand}_{r,l,f,y} = \frac{\text{SpecifiedAnnualDemand}_{r,f,y} * \text{SpecifiedDemandProfile}_{r,f,l,y}}{\text{YearSplit}_{y,l}}$

Capacity Adequacy A:

$\forall_{y,t,r}\text{AccumulatedNewCapacity}_{y,t,r} = \sum_{yy:y-yy<\text{OperationalLife}[t,r]\&\&y-yy\geq 0} \text{NewCapacity}_{yy,t,r}$

$\forall_{y,t,r}\text{TotalCapacityAnnual}_{y,t,r} = \text{AccumulatedNewCapacity}_{y,t,r} + \text{ResidualCapacity}_{y,t,r}$

$\forall_{y,t,l,r}\text{RateOfTotalActivity}_{y,l,t,r} = \sum_{m} \text{RateOfActivity}_{y,l,t,m,r}$

$\forall_{y,t,l,r}\text{RateOfTotalActivity}_{y,l,t,r} \leq \text{TotalCapacityAnnual}_{y,t,r} * \text{CapacityFactor}_{y,t,r} * \text{CapacityToActivityUnit}_{t,r}$

Capacity Adequacy B:

$\forall_{y,t,r} \sum_{l} \text{RateOfTotalActivity}_{y,l,t,r} * \text{YearSplit}_{y,l} \leq \text{TotalCapacityAnnual}_{y,t,r} * \text{CapacityFactor}_{y,t,r} * \text{AvailabilityFactor}_{y,t,r} * \text{CapacityToActivityUnit}_{t,r}$

Energy Balance A:

$\forall_{y,l,f,t,m,r}\text{RateOfActivity}_{y,l,t,m,r} * \text{OutputActivityRatio}_{y,t,f,m,r} = \text{RateOfProductionByTechnologyByMode}_{y,l,t,m,f,r}$

$\forall_{y,l,f,t,r}\text{RateOfProductionByTechnology}_{y,l,t,f,r} = \sum_{m} \text{RateOfProductionByTechnologyByMode}_{y,l,t,m,f,r}$

$\forall_{y,l,f,r}\text{RateOfProduction}_{y,l,f,r} = \sum_{t} \text{RateOfProductionByTechnology}_{y,l,t,f,r}$

$\forall_{y,l,f,t,m,r}\text{RateOfUseByTechnologyByMode}_{y,l,t,m,r} = \text{RateOfActivity}_{y,l,t,m,r} * \text{InputActivityRatio}_{y,t,f,m,r}$

$\forall_{y,l,f,t,r}\text{RateOfUseByTechnology}_{y,l,t,f,r} = \sum_{m} \text{RateOfUseByTechnologyByMode}_{y,l,t,m,f,r}$

$\forall_{y,l,f,r}\text{RateOfUse}_{y,l,f,r} = \sum_{t} \text{RateOfUseByTechnology}_{y,l,t,f,r}$

$\forall_{y,l,f,r}\text{Production}_{y,l,f,r} = \text{RateOfProduction}_{y,l,f,r} * \text{YearSplit}_{y,l}$

$\forall_{y,l,f,r}\text{Use}_{y,l,f,r} = \text{RateOfUse}_{y,l,f,r} * \text{YearSplit}_{y,l}$

$\forall_{y,l,f,r}\text{Demand}_{y,l,f,r} = \text{RateOfDemand}_{y,l,f,r} * \text{YearSplit}_{y,l}$

$\forall_{y,l,f,r}\text{Production}_{y,l,f,r} \geq \text{Demand}_{y,l,f,r} + \text{Use}_{y,l,f,r}$

Energy Balance B:

$\forall_{y,f,r}\text{ProductionAnnual}_{y,f,r} = \sum_{l} \text{Production}_{y,l,f,r}$

$\forall_{y,f,r}\text{UseAnnual}_{y,f,r} = \sum_{l} \text{Use}_{y,l,f,r}$

$\forall_{y,f,r}\text{ProductionAnnual}_{y,f,r} \geq \text{UseAnnual}_{y,f,r} + \text{AccumulatedAnnualDemand}_{y,f,r}$

Accounting Technology Production/Use:

$\forall_{r,l,t,f,y}\text{ProductionByTechnology}_{r,l,t,f,y} = \text{RateOfProductionByTechnology}_{r,l,t,f,y} * \text{YearSplit}_{l,y}$

$\forall_{r,l,t,f,y}\text{UseByTechnology}_{r,l,t,f,y} = \text{RateOfUseByTechnology}_{r,l,t,f,y} * \text{YearSplit}_{l,y}$

Total Max Capacity Constraints:

$\forall_{y,t,r}\mathrm{TotalCapacityAnnual}_{y,t,r} \leq \mathrm{TotalAnnualMaxCapacity}_{y,t,r}$

$\forall_{y,t,r}\mathrm{TotalCapacityAnnual}_{y,t,r} \geq \mathrm{TotalAnnualMinCapacity}_{y,t,r}$

New Capacity Constraints:

$\forall_{y,t,r}\mathrm{NewCapacity}_{y,t,r} \leq \mathrm{TotalAnnualMaxCapacityInvestment}_{y,t,r}$

$\forall_{y,t,r}\mathrm{NewCapacity}_{y,t,r} \geq \mathrm{TotalAnnualMinCapacityInvestment}_{y,t,r}$

Annual Activity Constraints:

$\forall_{y,t,r}\mathrm{TotalTechnologyAnnualActivity}_{y,t,r} = \sum_l \mathrm{RateOfTotalActivity}_{y,l,t,r} * \mathrm{YearSplit}_{y,l}$

$\forall_{y,t,r}\mathrm{TotalTechnologyAnnualActvity}_{y,t,r} \leq \mathrm{TotalTechnologyAnnualActvityUpperLimit}_{y,t,r}$

$\forall_{y,t,r}\mathrm{TotalTechnologyAnnualActvity}_{y,t,r} \geq \mathrm{TotalTechnologyAnnualActvityLowerLimit}_{y,t,r}$

Total Activity Constraints:

$\forall_{t,r}\mathrm{TotalTechnologyModelPeriodActivity}_{t,r} = \sum_y \mathrm{TotalTechnologyAnnualActivity}_{y,t,r}$

$\forall_{t,r}\mathrm{TotalTechnologyModelPeriodActivity}_{t,r} \leq \mathrm{TotalTechnologyModelPeriodActivityUpperLimit}_{t,r}$

$\forall_{t,r}\mathrm{TotalTechnologyModelPeriodActivity}_{t,r} \geq \mathrm{TotalTechnologyModelPeriodActivityLowerLimit}_{t,r}$

Emission Accounting:

$\forall_{r,t,m,y}\mathrm{TotalTechnologyActivityByMode}_{r,t,m,y} = \sum_l \mathrm{RateOfActivity}_{r,l,m,t,y} * \mathrm{YearSplit}_{l,y}$

$\forall_{y,t,e,m,r}\mathrm{AnnualTechnologyEmissionByMode}_{y,t,e,m,r} = \sum_l \mathrm{EmissionActivityRatio}_{y,t,e,m,r} * \mathrm{TotalAnnualTechnologyActivityByMode}_{r,t,m,y}$

$\forall_{y,t,e,r}\mathrm{AnnualTechnologyEmission}_{y,t,e,r} = \sum_m \mathrm{AnnualTechnologyEmissionByMode}_{y,t,e,m,r}$

$\forall_{y,t,e,r}\mathrm{AnnualTechnologyEmissionPenaltyByEmission}_{y,t,e,r} = \mathrm{AnnualTechnologyEmission}_{y,t,e,r} * \mathrm{EmissionPenalty}_{y,e,r}$

$\forall_{y,t,r}\mathrm{AnnualTechnologyEmissionPenalty}_{r,t,y} = \sum_e \mathrm{AnnualTechnologyEmissionPenaltyByEmission}_{r,t,e,y}$

$\forall_{r,t,y}\mathrm{DiscountedTechnologyEmissionPenalty}_{r,t,y} = \frac{\mathrm{AnnualTechnologyEmissionPenalty}_{r,t,y}}{(1+\mathrm{DiscountRate}_{r,t})^{(y-\mathrm{StartYear}+0.5)}}$

$\forall_{y,e,r}\mathrm{AnnualEmissions}_{y,e,r} = \sum_t \mathrm{AnnualTechnologyEmission}_{y,t,e,r}$

$\forall_{e,r}\mathrm{ModelPeriodEmissions}_{e,r} = \sum_y \mathrm{AnnualEmissions}_{y,e,r}$

$\forall_{y,e,r}\mathrm{AnnualEmissions}_{y,e,r} \leq \mathrm{AnnualEmissionLimit}_{y,e,r}$

$\forall_{e,r}\mathrm{ModelPeriodEmissions}_{e,r} \leq \mathrm{ModelPeriodEmissionLimit}_{e,r}$

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