



Defining Resilient Energy Pathways: A Modeling Framework to Address Uncertainty in Long-Term Planning

Valeria Baiocco^{*}, Emanuela Colombo^{}, Matteo Vincenzo Rocco^{}

Department of Energy, Politecnico di Milano, Milan 20156, Italy

Corresponding Author Email: valeria.baiocco@mail.polimi.it

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ABSTRACT

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Energy system transitions are inherently complex, requiring long-term planning to navigate uncertainties and achieve sustainability and resilience goals. Traditional energy modeling approaches often rely on assumptions of perfect foresight or utilize rolling horizon methods, which inadequately capture the dynamics of decision-making under imperfect foresight. This study introduces a multi-stage modeling framework designed to better represent real-world decision-making under uncertainty by revising forecasts and updating decisions throughout the planning horizon. A pilot model is developed and applied to a case study using historical data on power sector development, serving as an initial test of the framework's applicability. Results suggest that this approach provides a more realistic representation of decision-making processes in energy planning and warrants further exploration for improving long-term energy system planning and investment strategies under uncertainty.

1. INTRODUCTION

Energy system transitions at the National level are inherently complex and gradual processes. Whether aiming to enhance sustainability or improve system resilience, transforming an energy, such change cannot be achieved overnight, it requires coordinated long-term planning [1, 2]. Ambitious policy targets, such as Italy's National Energy and Climate Plan (PNIEC) [3], which aims to decarbonize the power sector by 2050, require strategic, long-term planning and a stepwise transformation of infrastructure and technologies [1, 4]. Given the long lead times for building generation capacity, expanding grid infrastructure, and developing new energy markets, decisions made today will shape the system for decades to come [1].

To support such planning, long-term energy models are essential [2]. However, modelling over multi-decade horizons presents a significant challenge: there is no reliable way to accurately predict future data [4-6]. Critical inputs such as energy demand, technology costs, and fuel prices are highly uncertain, and their evolution depends on a multitude of interdependent factors, including socio-economic trends, technological breakthroughs, policy shifts, and global events, many of which are unpredictable or unknowable in advance [1, 4, 7].

One important aspect that appears underrepresented in many energy modelling frameworks for long-term planning is the role of decision-making under imperfect foresight. In reality, decisions, such as infrastructure investments or policy interventions, are made based on expectations about the future, typically derived from current forecasts [8]. However, as such decisions involve long lead times and irreversible

commitments, they are often implemented before the actual future unfolds. This can result in systems being built on assumptions that do not align with how conditions evolve in practice, leading to suboptimal outcomes. Compounding this issue is the fact that many models are inherently static [4], offering limited ability to revise or adapt decisions once a pathway has been selected. Bridging this gap requires modelling approaches that can represent multi-stage decision-making under imperfect foresight, where decisions are based on forecasted expectations but can be revised over time as new information becomes available, better capturing the dynamic and uncertain nature of real-world energy transitions.

This research aims to explore a novel approach for modeling decision-making horizons to better represent decision-making under imperfect foresight. To this end, a multi-stage modeling framework is proposed and implemented in a pilot model, aiming to assess whether it is a promising approach for more realistically representing real-world planning processes.

The structure of the paper is as follows: Section 2.1 outlines existing modelling approaches, Section 2.2 presents the proposed framework, Section 3 discusses preliminary results, and Section 4 concludes with key findings and limitations.

2. METHODOLOGY

2.1 Existing modelling approaches

In energy models, future knowledge in decision-making is typically assumed to be either fully known in perfect foresight models or limited, with a certain degree of myopia, in rolling horizon models.

Perfect foresight models assume complete certainty over future parameters, enabling single-stage optimization that yields an optimal pathway under fully deterministic conditions [8, 9]. The assumption of perfect foresight does not reflect real-world decision making where knowledge of the future is imperfect and uncertain.

Rolling horizon modeling divides the time horizon subset horizons said planning horizons. Decisions are made for the entire planning horizons, but only a portion, corresponding to the fixed horizon (FH), is implemented and becomes irreversible. The planning horizon is then shifted forward by the length of the fixed horizon, at which point additional information along the timeline becomes available, and the optimization problem is re-evaluated accordingly. This iterative process is repeated until the end of the overall planning horizon is reached [10]. While perfect foresight assumes full knowledge of future developments, rolling horizon models introduce myopia based on the fixed and planning horizon lengths. Shorter horizons focus more on short-term decisions, however these models don't explicitly account for decision-making under imperfect foresight, limiting their ability to capture forecast uncertainty and its structural impact.

Additionally, the only widely used approach for multistage modeling in energy systems is linked to stochastic optimization, which addresses optimization under uncertainty. While it can partially handle imperfect foresight, it is primarily reliant on probabilistic functions [7]. However, in cases of deep uncertainty, these probabilistic functions may not be well-defined, limiting the method's applicability.

2.2 Proposed framework

The model is based on Input–Output (IO) theory, employing a bottom-up Rectangular Choice of Technologies (RCOT) Supply-and-Use Table (SUT) framework that captures the detailed flow of energy and resources across sectors. While this framework is typically implemented with annual resolution, it has been adapted to operate at an hourly resolution to more accurately capture the temporal variability of renewable energy sources.

The full set of equations can be found in previous study [11].

2.2.1 RCOT-SUT framework

The SUT-based framework was selected over traditional equation-based energy modeling approaches due to its structural flexibility. While it maintains the same linear relationships as conventional models, ensuring supply equals demand within capacity and operational constraints, its formulation differs. Rather than using explicit energy balance equations, the SUT framework employs a matrix representation of production and consumption flows across sectors. Although the current focus is on the power sector, the model aims to eventually encompass all productive sectors connected to the electricity system, providing a more comprehensive view of the power system's transition. The SUT framework also allows for the integration of additional sectors and the application of differentiated temporal resolutions, such as using hourly granularity where necessary, to reduce computational complexity while ensuring system-wide consistency. Furthermore, it offers robust tracking of emissions, labor, taxes, and other factors, accounting for them by sector activity or product demand [12].

The matrix representation of the SUT framework is structured around two primary components: sectors, which represent the production and consumption technologies; and products, which correspond to the commodities exchanged within the system. The model adopts an industry-based assumption, where each commodity is produced by a fixed combination of technologies. Additionally, the RCOT approach allows for selected commodities to be supplied by competing technologies, thereby introducing substitution dynamics into the supply structure.

2.2.2 Adaptation of RCOT-SUT to energy modelling

To the basic SUT structure, additional equations are incorporated to form the RCOT-SUT structure. The principle of RCOT is that it allows technologies producing different products to compete with each other. This is used to model competing generation technologies in the power sector. To adapt the SUT framework for energy models, further equations are typically added to account for the unique characteristics of energy systems.

Curtailment: For production technologies, the possibility of energy curtailment is considered to account for overproduction by renewable energy sources. To model this, an additional variable representing curtailment is introduced into the energy supply-use balances, ensuring that excess energy generation from renewables is appropriately accounted for in the system.

Energy balances: Production is constrained by available capacity, with additional limits defined through technology-specific load factors at both hourly and annual levels. Hourly constraints are applied to variable renewable generation technologies to reflect their temporal variability and intermittency. Annual constraints account for broader operational limitations, such as scheduled maintenance or downtime.

Capacity constraints: The model incorporates endogenous capacity expansion for power technologies, treating total installed capacity as a decision variable. Several capacity-related variables, defined on a yearly basis, are introduced to represent different aspects of the system:

- Operative Capacity (Cap_{op}): Capacity available for production in a given year.
- Disposed Capacity (Cap_{disp}): Capacity decommissioned in a given year, modeled using a Weibull disposal function.
- Built Capacity (Cap_{built}): Capacity that completes construction and becomes operational in a given year.

The yearly update of operative capacity, given a year y is governed by the following equation:

$$Cap_{op}(y) = Cap_{op}(y - 1) + Cap_{built}(y) - Cap_{disp}(y) \quad (1)$$

The planning model incorporates the temporal dynamics of capacity development. This involves two key time factors:

- Decision to Construction Time (dc): This represents the time between the decision to expand capacity and the actual financing required to begin construction.
- Construction to Operation Time (co): This captures the time between when capacity is financed and when it becomes operational.

Once an investment decision is made, the corresponding capacity is denoted as $Cap_{planned}$. After the dc elapses, the capacity enters the financing phase and is recorded as $Cap_{financed}$. Following the co , the capacity becomes operational and is referred to as Cap_{built} .

Costs: The model accounts for several cost components associated with electricity generation and capacity expansion. These include variable operation and maintenance costs (c_{var}), fixed operation and maintenance costs (c_{fix}) and capacity investment costs (c_{inv}). All costs are discounted over the planning horizon using a predefined discount rate to reflect the time value of money, ensuring consistency in cost comparison across years.

Objective: The objective of the model is to minimize the total system cost over the planning horizon.

$$Min(Z) = c_{inv}Cap_{financed} + c_{var}X + c_{fix}C_{op} \tag{2}$$

where, X is the total technology activity.

Multistage time horizons: The model’s time horizon is managed using a multi-stage framework that builds upon and extends the rolling horizon approach. Given a modeling time

horizon from a starting year Y_1 to a final year Y_n , set of $z = 0, 1 \dots, x$ stages are defined, according to a certain fixed horizon length δ , such that

$$x = \frac{Y_n - Y_1}{\delta} \tag{3}$$

Each z stage is characterized by a planning horizon (PH_z) with a length l of:

$$l = Y_1 - Y_n - \delta z \text{ with } z = 0, \dots, x \tag{4}$$

This formulation allows each stage to optimize decisions over a progressively shorter planning horizon as the model advances through time. A comparison with conventional perfect foresight and rolling horizon approaches is illustrated in Figure 1.

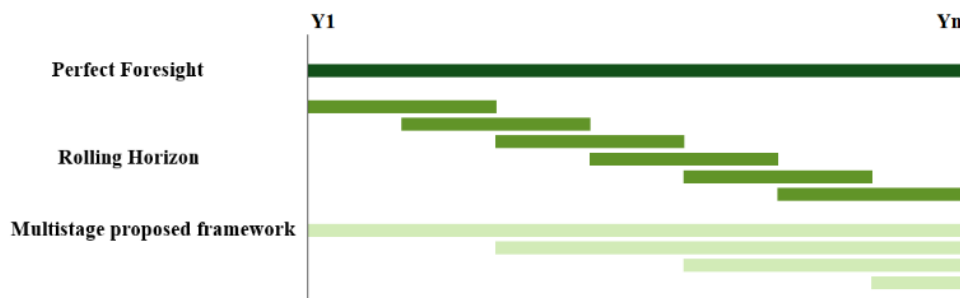


Figure 1. Comparison of planning horizon concepts

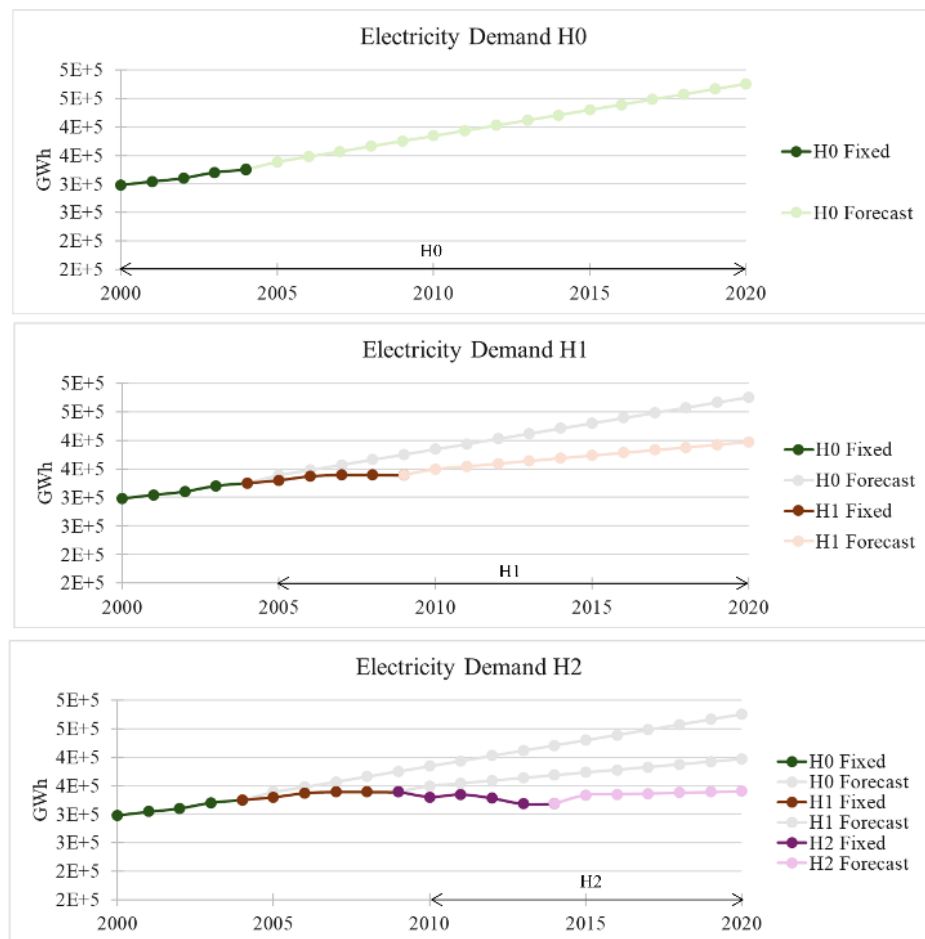


Figure 2. Electricity demand at different stages

In each planning horizon (PH_z), two sub-horizons are defined:

- Fixed Horizon ($FH_z(\delta)$): Covers the first δ years of the P-H. Within this period, electricity demand is assumed to be known with certainty, and system operation and capacity construction decisions are treated as fully informed and therefore finalized and irreversible.

- Investment Horizon ($IH_z(\epsilon)$): Extends ϵ years beyond FH_z . During this interval, capacity expansion decisions are made based on forecasted demand profiles, which are subject to uncertainty and may diverge from realized future values. Nonetheless, due to the long development lead times associated with energy infrastructure investment decisions must be made proactively. To capture the commitment effect of early-stage financing, any capacity that is committed within this ϵ -period ($Cap_{financed}$) is considered irreversible and is assumed to result in actual capacity deployment (Cap_{built}) in future stages. Operational dispatch for the investment horizon is not yet optimized; these decisions are deferred and will be determined in the corresponding fixed horizon of a later stage, once demand becomes fully observed.

Electricity demand: In this initial implementation of the model, electricity demand is the only parameter subject to uncertainty, and thus the sole source of imperfect foresight. Each stage operates with a stage-specific electricity demand trajectory, which is revised at the beginning of the stage. Within the fixed horizon (FH), representing the short-term window, demand is assumed to be perfectly known and fixed. Beyond FH , demand is treated as a forecast, subject to revision in subsequent stages. After each stage is optimized, the model advances to the next stage, and the demand forecast is updated based on newly available information. In this version, forecast revisions are applied exogenously, using predefined adjustments to reflect changes in expectations. Future model developments will aim to endogenize this process, updating demand projections dynamically based on outcomes from previous stages. Figure 2 illustrates the stage-by-stage evolution of electricity demand as applied in the case study.

Rolling mechanism: The multi-stage modeling framework allows for the implementation of a rolling mechanism that distinguishes between short-term operational commitments and long-term planning flexibility, reflecting the reality of imperfect foresight in energy system planning. At each planning stage, decisions are categorized based on their temporal proximity and reversibility.

Operational decisions: Capacity construction (Cap_{built}) and system operation locked in during the fixed horizon $FH(\delta)$, where data is assumed to be accurate. These decisions are treated as fully implemented and thus irreversible.

Financing commitments: Capacity financing ($Cap_{financed}$) that occurs within the investment horizon ($IH(\epsilon)$). This reflects the assumption that once capacity is financially committed, it is effectively under construction, and thus cannot be revised in subsequent stages, even if updated demand forecasts diverge from initial projections.

Long-term plans: Capacity planning ($Cap_{planned}$) whose financing is scheduled beyond the I-H. As the investment is not yet committed, the remain reversible and are subject to re-evaluation in the following stages.

After a stage z is optimized, the model advances to the next stage $z + 1$. At this point:

- The electricity demand profile is updated based on newly available information.

- Operational capacity and dispatch decisions from the fixed horizon ($FH_z(\delta)$) are fixed and carried forward as implemented.

- Investment decisions that fell within the investment horizon $IH_z(\delta + \epsilon)$ are treated as financially committed. Those financed within $IH_z(\delta)$ are treated as under construction, while those scheduled within the extended window $IH_z(\delta + \epsilon)$ are assumed to soon enter the construction phase, and are thus also treated as irreversible in subsequent stages.

A schematic representation of the multistage flow of information and decisions is provided in Figure 3.

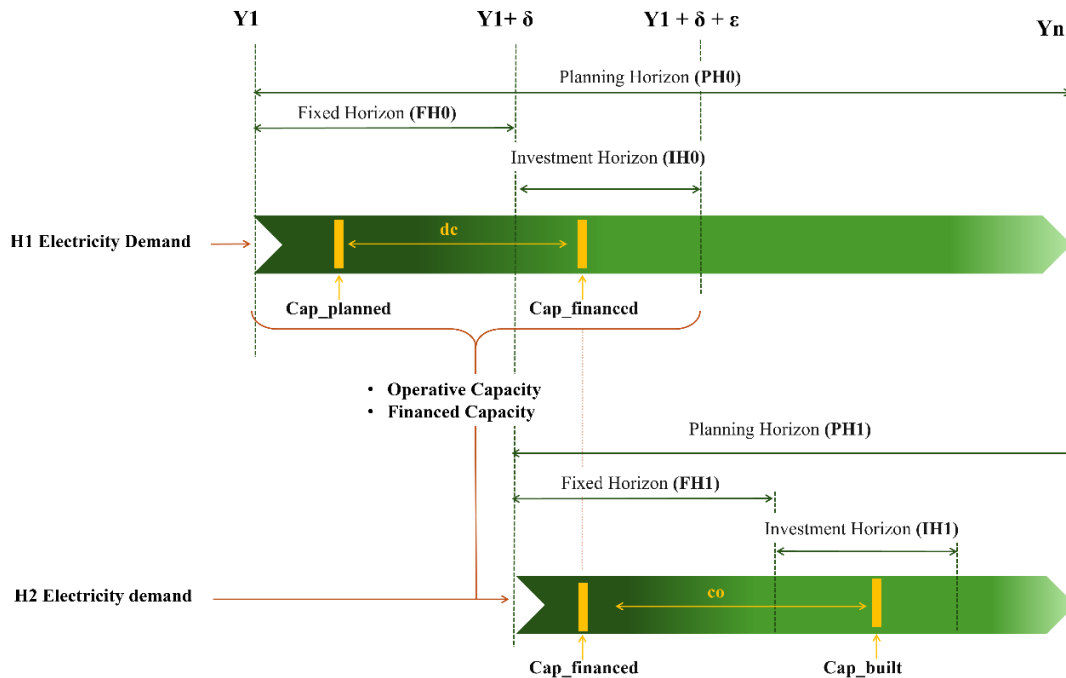


Figure 3. Schematic representation of proposed framework

3. CASE STUDY

To evaluate the practical relevance of the proposed multistage framework, the model was applied to a retrospective case study of the Italian electricity system from 2000 to 2025. This period is characterized by evolving demand projections, shifting policy priorities, and significant expansion in renewable generation, making it a suitable testbed to explore how long-term planning decisions are affected by imperfect foresight.

The objective of the case study is twofold:

- First, to demonstrate the limitations of perfect foresight assumptions in replicating real-world decisions.
- Second, to evaluate whether the proposed multistage model, even in a simplified form, offers a structurally more realistic representation of decision-making under uncertainty.

Two distinct model configurations were executed: a single-stage optimization assuming perfect foresight, and the proposed multistage imperfect foresight framework. Model outputs—specifically installed capacity, decommissioned capacity, and total electricity supply—were compared against historical data to evaluate the proposed framework’s capability to accurately replicate the temporal evolution of the energy system under varying information assumptions.

3.1 Model inputs

The complete dataset of input parameters and assumptions used in the model, including demand profiles, technology characteristics, and cost assumptions, can be found in previous study [11].

Model resolution: For this initial pilot, an annual resolution was adopted, defining a yearly energy balance and average technology capacity factors based on historical data [13]. A Modelling horizon ranging from 2000 to 2020 was selected.

Multistage horizon: A multistage decision framework was applied, with a fixed horizon of length $\delta = 5$ years. This choice reflects the assumption that energy planners typically have a relatively high level of confidence in demand projections over the short-to-medium term. This choice is supported by

empirical comparisons between forecasted and realized demand data, which show that projections over the first three to five years typically exhibit a high degree of accuracy and alignment. An investment horizon extension of $\varepsilon = 4$ years was added, calibrated through preliminary model testing. This brings the total planning horizon per stage to $\delta + \varepsilon = 9$ years, which aligns with literature findings suggesting that major infrastructure decisions are generally reassessed every 5 to 10 years [8].

Electricity demand: In the single-stage perfect foresight model, electricity demand is represented by the actual historical demand trajectory. Conversely, in the multistage imperfect foresight framework, demand forecasts at the beginning of each decision stage (e.g., 2000, 2005, 2010, etc.) are based on the official projections available at the time, as reported in previous study [13].

3.2 Results

Results indicate that the proposed multistage imperfect foresight framework more accurately replicates historical trends compared to the baseline single-stage perfect foresight model. In terms of installed capacity, as shown in Figure 4, the perfect foresight model systematically underestimates investments. This outcome is expected, as perfect knowledge of future demand allows the model to optimize investments precisely to match needs, avoiding overcapacity. Conversely, the multistage imperfect foresight model yields higher installed capacity levels, closer to observed historical data. This outcome underscores the influence of forecast uncertainty on investment dynamics. In particular, historical trends in the early 2000s show that projected electricity demand was significantly overestimated compared to what ultimately materialized. Consequently, substantial investments in natural gas capacity were undertaken based on these inflated expectations. By the time it became apparent that actual demand growth would be more modest, many of these projects had already been initiated or financially committed, resulting in a persistent oversupply of capacity.

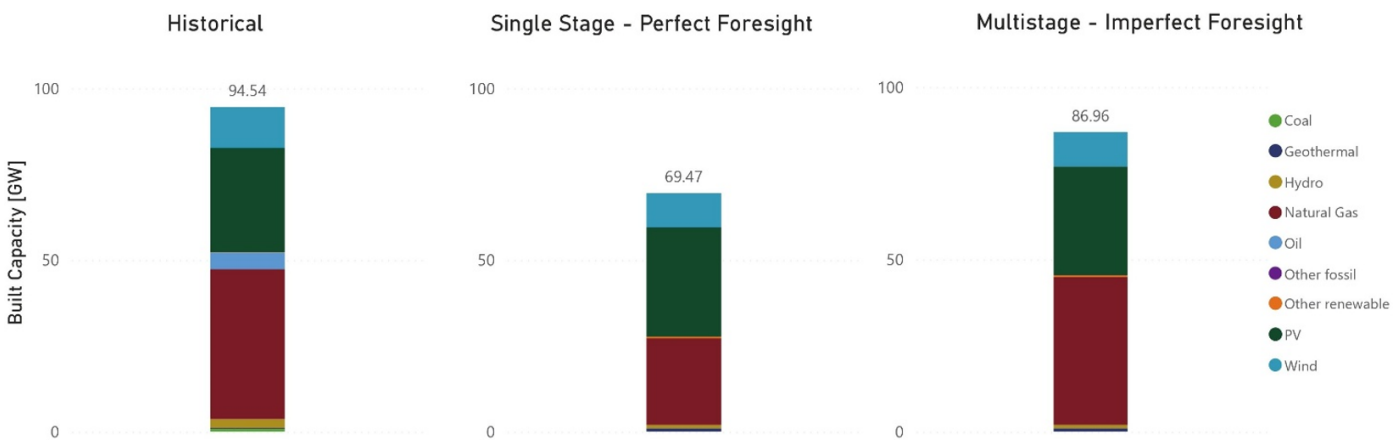


Figure 4. Total built capacity

The overcapacity situation leads to higher total system costs in the imperfect foresight model compared to the perfect foresight case, as show in Figure 5. While the overall cost difference is relatively small, it highlights the increased financial risk for investors in power plants that operate below expected capacity. Lower utilization rates cause longer

payback times and greater uncertainty in returns, making it particularly challenging for single-asset power producers who lack diversified portfolios.

A comparison of annual electricity supply between the two model configurations indicates that both exhibit similar dispatch behavior, as shown in Figure 6. In the multistage

imperfect foresight model, excess capacity does not significantly alter dispatch quantities but results in higher reserve margins. Compared to historical data, both models tend to slightly overestimate renewable generation and underrepresent the substitution dynamics between natural gas and oil-fired generation. These discrepancies primarily arise from the model's limited temporal resolution, which currently relies on a single representative day per year. This simplification limits the ability to capture intra-annual variability, operational constraints such as ramping capabilities, and the full flexibility requirements of different technologies. Increasing temporal granularity, such as incorporating multiple representative days through clustering, and incorporating operational constraints would enhance dispatch accuracy and more realistically capture the operational behavior of the power system.

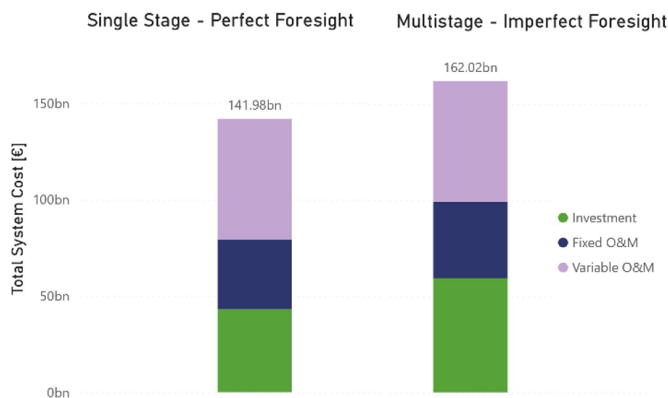


Figure 5. Total system costs

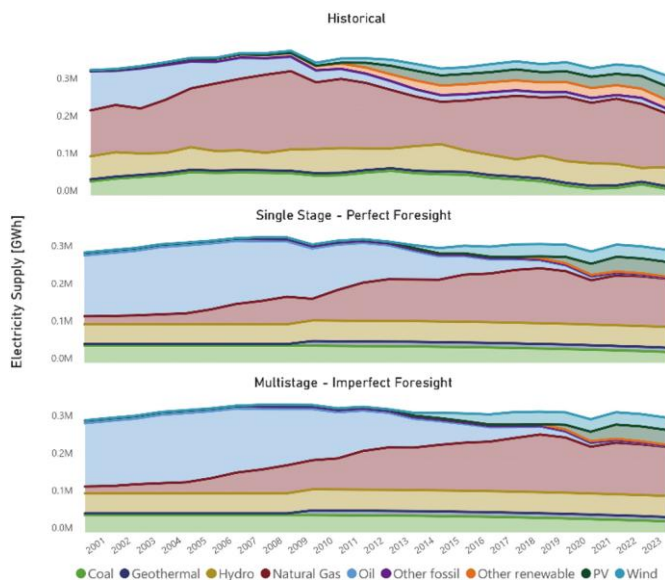


Figure 6. Yearly system supply

4. CONCLUSIONS AND FUTURE WORK

This study introduced a multistage investment-planning model that explicitly accounts for electricity demand forecast uncertainty and benchmarked its outputs against both a conventional perfect foresight formulation and observed historical developments. The results demonstrate that imperfect foresight, while yielding suboptimal outcomes from a cost-efficiency perspective, provides a more realistic

representation of decision-making under uncertainty. In the context of the analyzed case study, this outcome is strongly influenced by demand overestimations in the early 2000s, which led to forward-looking investments that became financially locked in before actual demand trajectories were fully revealed. As a result, the imperfect foresight model more accurately replicates historical capacity development but at the cost of higher system expenditures and lower asset utilization. These findings highlight the systemic impact of forecast uncertainty and emphasize the associated financial risks borne by investors, especially in the context of capital-intensive technologies with long payback periods.

Future research will build on this foundation to explore how different modeling assumptions and structural factors influence investment outcomes under uncertainty. Key developments will include enhancing the model's temporal resolution by incorporating multiple representative periods per year to better capture variability in load, renewables, and operational flexibility constraints. Spatial detail will also be added by introducing a simplified transmission network to explore regional disparities in resource availability and grid congestion. Building on this refined framework, future analysis will focus on developing indicators to identify which technologies are most vulnerable to forecast uncertainty, and how techno-economic characteristic, such as capital intensity, ramping capability, and dispatchability, affect their resilience. The ultimate objective is to inform strategies that mitigate the adverse impacts of forecast errors, enhancing the robustness of investment decisions and system planning.

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REFERENCES

- [1] Saraji, M.K., Streimikiene, D. (2023). Challenges to the low carbon energy transition: A systematic literature review and research agenda. *Energy Strategy Reviews*, 49: <https://doi.org/10.1016/j.esr.2023.101163>
- [2] Pfenninger, S., Hawkes, A., Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, 33: 74-86. <https://doi.org/10.1016/j.rser.2014.02.003>
- [3] Ministero dell'Ambiente e Sicurezza Energetica. (2024). Piano Nazionale Integrato per L'Energia e il Clima (PNIEC). https://www.mase.gov.it/sites/default/files/archivio/pniec_finale_17012020.pdf.
- [4] Fodstad, M., del Granado, P.C., Hellemo, L., Knudsen, B.R., et al. (2022). Next frontiers in energy system modelling: A review on challenges and the state of the art. *Renewable and Sustainable Energy Reviews*, 160: 112246. <https://doi.org/10.1016/j.rser.2022.112246>
- [5] Debnath, K.B., Mourshed, M. (2018). Challenges and gaps for energy planning models in the developing-world context. *Nature Energy*, 3(3): 172-184. <https://doi.org/10.1038/s41560-018-0095-2>
- [6] Chang, M., Thellufsen, J.Z., Zakeri, B., Pickering, B., Pfenninger, S., Lund, H., Østergaard, P.A. (2021).

- Trends in tools and approaches for modelling the energy transition. *Applied Energy*, 290: 116731. <https://doi.org/10.1016/j.apenergy.2021.116731>
- [7] Yue, X., Pye, S., DeCarolus, J., Li, F.G., Rogan, F., Gallachóir, B.Ó. (2018). A review of approaches to uncertainty assessment in energy system optimization models. *Energy Strategy Reviews*, 21: 204-217. <https://doi.org/10.1016/j.esr.2018.06.003>
- [8] Nerini, F.F., Keppo, I., Strachan, N. (2017). Myopic decision making in energy system decarbonisation pathways. A UK case study. *Energy Strategy Reviews*, 17: 19-26. <https://doi.org/10.1016/j.esr.2017.06.001>
- [9] Lambert, J., Hanel, A., Fendt, S., Spliethoff, H. (2023). Evaluation of sector-coupled energy systems using different foresight horizons. *Renewable and Sustainable Energy Reviews*, 184: 113562. <https://doi.org/10.1016/j.rser.2023.113562>
- [10] Cuisinier, É., Lemaire, P., Penz, B., Ruby, A., Bourasseau, C. (2022). New rolling horizon optimization approaches to balance short-term and long-term decisions: An application to energy planning. *Energy*, 245: 122773. <https://doi.org/10.1016/j.energy.2021.122773>
- [11] Valeria Baiocco, E.S. (2025). Model Repository. AIGE. https://github.com/valebii/cvxlab_rh_dev/tree/AIGE.
- [12] Miller, R.E., Blair, P.D. (2009). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press.
- [13] Terna. Pubblicazioni Statistiche. <https://www.terna.it/it/sistema-elettrico/statistiche/pubblicazioni-statistiche>.

NOMENCLATURE

<i>PH</i>	Planning horizon
<i>FH</i>	Fixed horizon
<i>IH</i>	Investment horizon
<i>Cap</i>	Technology capacity
<i>dc</i>	Decision to construction time
<i>co</i>	Construction to operation time
<i>c</i>	Specific costs
<i>Z</i>	Objective
<i>X</i>	Total technology activity
<i>x</i>	Number of stages
<i>Y</i>	Year

Greek symbols

δ	Fixed horizon length
ε	Investment horizon extension

Subscripts

<i>z</i>	Stage number
<i>n</i>	Last year of modelling horizon
<i>planned</i>	Planned capacity
<i>built</i>	Built capacity
<i>financed</i>	Financed capacity
<i>op</i>	Operative capacity
<i>disp</i>	Disposed capacity
<i>var</i>	Variable costs
<i>fix</i>	Fixed costs