Assignment 2

A Consulting Perspective on Power System Decision-Making: Modeling, Strategy, and Optimization

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Table 1: Individual participation in %

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Nomenclature

Parameters

α_m	Price discount factor for block m (e.g. 1.00, 0.85, 0.60) (Model 3)
η_j	Efficiency / capacity factor of technology j
$\gamma_j^{CO_2}$	Emission factor [tCO_2/MWh] (Model 3)
$\gamma_{j,t,s}$	Capture factor for technology j, period t, scenario s (Model 3)
$\mathcal{J}$	Set of technologies
$\mathcal{S}$	Set of scenarios (Model 3)
$\mathcal{T}$	Set of time periods
$\overline{K}_j$	Maximum cumulative installable capacity for tech j [MW]
$\tau_t^{CO_2}$	CO_2 price in period t [MEUR/tCO_2] (Model 3)
B^{init}	Initial available budget [MEUR]
c_j^{cap}	Specific capital expenditure (CAPEX) cost [MEUR/MW]
D_t	Electricity demand in period t [MWh]
f_j	Fixed O&M cost [MEUR/MW]
H	Operating hours per year (8760 h)
m	Index of demand-price blocks, $m \in \{1, 2, 3\}$
p_t	Electricity price in period t (Model 2) [MEUR/MWh]
$p_{t,s}$	Electricity price in period t, scenario s (Model 3) [MEUR/MWh]
$Q_t^{(m)}$	Maximum energy sold in block m in period t (Model 3)
v_j	Variable O&M cost [MEUR/MWh]

Decision Variables

B_t	Available budget in period t (Model 2) [MEUR]
$B_{t,s}$	Available budget in period t, scenario s (Model 3) [MEUR]
C_t^{cap}	CAPEX cost in period t [MEUR]
C_t^{fix}	Fixed O&M cost in period t [MEUR]

C_t^{op}	Variable operating cost in period t (Model 2) [MEUR]
$C_{t,s}^{\mathrm{op}}$	Scenario-dependent operating cost (incl. CO_2) [MEUR]
$e_{j,t,s}$	Energy produced by tech j in period t, scenario s (Model 3) [MWh]
$e_{j,t}$	Energy produced by tech j in period t (Model 2) [MWh]
$i_{j,t}$	New investment in technology j in period t [MW]
$k_{j,t}$	Cumulative installed capacity of technology j in period t [MW]
$q_{t,s}^{(m)}$	Energy sold in block m in period t, scenario s [MWh] (Model 3)
R_t	Revenue in period t (Model 2) [MEUR]
$R_{t,s}$	Revenue in period t, scenario s (Model 3) [MEUR]

1 Introduction

This report contains the implementation and analysis of a modeling roadmap designed to support investment and operational decision-making for a diversified electricity producer. Building on the consulting proposal, we develop a sequence of optimization models that progressively incorporate intertemporal dynamics, uncertainty, carbon pricing, and competitive market effects. The objective is to evaluate how modeling assumptions influence investment strategies, operational behaviour, and financial performance.
The modeling structure is based on three models, each of which builds on the previous one and provides increasingly more information. Model 1 provides a deterministic basis which, through myopic analysis, identifies the most cost-effective technology under ideal conditions and annualised cost assumptions. Model 2 extends this basis by adding a time horizon, shifting the focus to long-term revenue maximisation, taking into account the dynamic evolution of investment decisions, capacity building and budget availability over time. Model 3, as the most advanced, adds an element of uncertainty by analysing scenarios that are randomly generated based on historical or forecast data and are not linked to clearly defined probability distributions. Together, these models form a coherent path from transparent baseline comparisons to dynamic financial planning, ending with decision-making under real-world uncertainty.
The report is structured as follows. Section 2 summarises the data sources and scenario generation approach. Section 3 presents the three model formulations and key assumptions, including the validation and experiment design. Section 4 compares results across the modeling stages, with a detailed analysis of the stochastic formulation. Section 5 discusses limitations and modeling trade-offs. Section 6 concludes with actionable recommendations for the client.

All code developed for this project is publicly available in our `Github repository`.

2 Data

This project uses four main data categories: technology parameters, electricity price paths, demand assumptions, and carbon- and policy-related inputs.

Technology data. Cost and performance parameters (CAPEX, variable O&M, fixed O&M, efficiency, lifetime) for all technologies are taken from the Danish Energy Agency's Technology Catalogue [1].

Electricity prices. The power-price trajectory is sourced from the Danish Ministry of Climate, Energy and Utilities DK2 projection [2], converted to EUR/MWh (fixed rate 7.4). This series is used directly in Model 2 and as the baseline for stochastic scenario generation in Model 3.

Demand. As a baseline, the 2024 Danish electricity demand reported by the IEA [3] is used. Applying an assumed targeted market share of 10% yields an initial demand level of 3,525,000 MWh.

Carbon data. CO_2 intensities are taken from PyPSA's 2030 technology dataset. The carbon price follows EU ETS permit values, using the latest quoted price from TradingEconomics [4] as the initial level (83 EUR/tCO_2), increasing linearly by 5 EUR/year.

Capacity benchmarks. ENTSO-E net installed capacity data are used to impose realistic expansion limits. Each technology may build up to 20% of the total national capacity scaled by the assumed market share.

Model parameters. All models use 8760 hours/year. Initial budgets is 150 MEUR. A net revenue factor of 0.7 is applied to reflect tax, grid- and balancing-related deductions.

Stochastic inputs (Model 3). Price uncertainty is generated via 100 AR(1)-type scenarios with 15% volatility. Technology-specific capture factors follow a similar bounded AR(1) process. A three-block market structure is included, with block quantities set to $(0.25, 0.35, 0.40)$ of annual demand and block prices defined as fixed proportions of scenario prices.

3 Methodology

3.1 Model 1 - Static Cost-Based Optimal Technology Mix

The objective function of this optimization model minimizes the total annual system cost, which includes both the annualized investment expenditure for installed capacity, annualized fixed operation and maintenance costs and the variable operation and maintenance costs associated with energy production. By doing so, the model seeks the most cost-efficient technology mix to meet energy needs.

Objective Function:

$$\min_{x_j,\ E_j,\ y_j} \quad \sum_{j \in \mathcal{J}} \left(\frac{c_j^{\text{inv}}}{L_j} \cdot x_j + c_j^{\text{var}} \cdot E_j + \frac{c_j^{fix}}{L_j} \cdot y_j \right)$$

The full set of constraints for model 1 is given in Appendix A .

3.2 Model 2 - Dynamic Investment and Revenue Optimization

Model 2 extends the baseline formulation by incorporating a multi-period planning horizon and shifting the focus from cost minimization to revenue maximization. It captures the dynamic evolution of investment decisions, capacity accumulation, and budget availability over time. Electricity prices, demand, and revenues vary across periods, creating a time-dependent decision environment. Investments in earlier periods influence future production capabilities and financial flexibility. This formulation better reflects real-world strategic energy planning under evolving market conditions.

Objective Function:

$$\max_{\substack{i_{j,t}, k_{j,t}, e_{j,t}, \\ B_t, R_t, C_t^{\text{op}}, C_t^{\text{fix}}, C_t^{\text{cap}}}} \quad \sum_{t \in \mathcal{T}} \left(R_t - C_t^{\text{op}} - C_t^{\text{fix}} - C_t^{\text{cap}} \right)$$

The full set of constraints for the deterministic model is given in Appendix B .

3.3 Model 3 - Market and Policy Uncertainty

Model 3 builds on the dynamic investment framework of Model 2 by explicitly representing uncertainty in electricity market prices and internalizing a technology-specific carbon tax in the operating costs. In contrast to the deterministic setting, revenues and variable costs now depend on a set of price scenarios that are generated randomly from historical or forecasted data, rather than being associated with explicitly defined probability distributions. Investment and capacity decisions remain here-and-now choices that must be robust across all scenarios, whereas generation and budget trajectories adapt ex post to the realized prices. This stochastic formulation allows us to assess the economic performance of a given investment strategy under volatile market conditions and stricter climate policy. In addition, Model 3 incorporates a simple representation of competitiveness in the electricity market. We assume that the effective selling price decreases stepwise as the producer's share of the total demand in each period increases: the first 25% of the total demand D_t served is sold at the full market price, the next 50% at a 15% discounted price, and any energy beyond 75% of demand at a 40% discounted price.

Let $\mathcal{S}$ denote the set of price scenarios, indexed by s, each representing a plausible realization of the multi-period electricity price trajectory. All scenarios are treated equally in the optimization, so that the model effectively maximizes the sample-average profit over the simulated futures. Carbon pricing is represented through a uniform carbon tax τ^{CO_2} [MEUR/tCO$_2$] and technology-specific emission factors γ_j [tCO$_2$/MWh]. To model the volume-dependent pricing, we introduce auxiliary variables $q_{t,s}^{(m)}$, $m = 1, 2, 3$, denoting the energy sold in three demand tranches in period t and scenario s.

Objective Function:

$$\max_{\substack{i_{j,t}, k_{j,t}, e_{j,t,s}, \\ q_{t,s}^{(m)}, B_{t,s}, R_{t,s}, \\ C_{t,s}^{\text{op}}, C_t^{\text{fix}}, C_t^{\text{cap}}}} \quad \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} \left(R_{t,s} - C_{t,s}^{\text{op}} - C_t^{\text{fix}} - C_t^{\text{cap}} \right)$$

The full constraint formulations of Model 3, including all investment, dispatch, budget and block-market constraints, is provided in Appendix C.

Overall, Model 3 yields an investment and operation strategy that maximizes the average profit over a large set of randomly generated price scenarios while explicitly penalizing carbon-intensive technologies through a technology-specific carbon tax and capturing the loss of price due to increased market penetration. Compared to Model 2, this leads to lower exposure to downside price risk, a systematic shift towards low-emission technologies, and a more realistic trade-off between market share and unit revenue.

4 Results

This section presents the optimisation outcomes across the three models, highlighting how technology choices, investment patterns, and system costs evolve as additional dynamics and uncertainties are introduced.

4.1 Final Technology Mix Across Models

The three models produce distinctly different technology portfolios, reflecting their underlying assumptions about information, investment flexibility, and market uncertainty. Model 1, the deterministic baseline, selects a balanced mix of gas, onshore wind, and PV, each contributing roughly 28%, with diesel providing the remaining 15%. This reflects purely cost-optimal choices under perfect information. Model 2 introduces intertemporal investment and revenue-driven decision-making, which results in a uniform capacity build-out: gas, diesel, onshore wind, and PV each reach approximately 25% of total installed capacity. The optimisation model thereby detects the cheapest chronological order of technologies, increases installed capacity until the maximum capacity constraint is reached, and then starts investing in the next-best technology, resulting in a uniform distribution and a smooth budget evolution. In contrast, Model 3 incorporates market uncertainty and technology-specific variability. Here, the optimal portfolio shifts substantially toward renewables: PV dominates with 58.8%, followed by onshore wind at 14%, while gas provides the remaining 27.2%. Diesel is not selected at all. This shift reflects two key effects: the asymmetric risk profile of technologies, as PV and wind maintain stable positive margins across most scenarios, while fossil assets face exposure primarily to rising carbon prices. Notably, PV reaches its imposed cumulative capacity limit, indicating that under uncertainty it becomes the dominant risk-adjusted investment option. Figure 1 displays the resulting, final portfolio mix across the developed models.

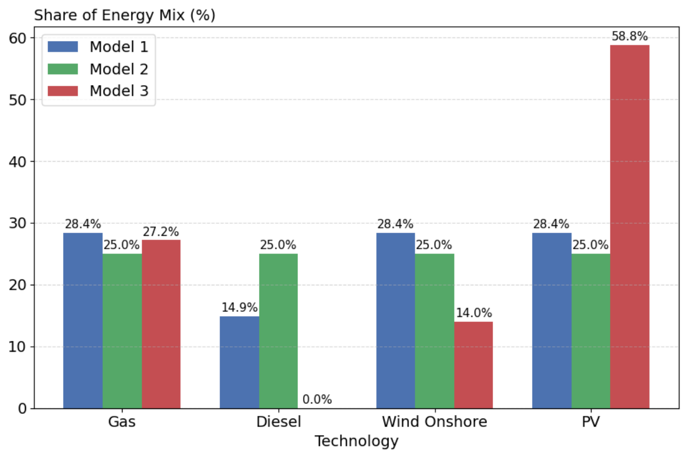

Figure 1: Technology share of installed capacity across Models 1–3

Table 2: Comparison of key results for Model 2 and Model 3

Metric	**Model 2**	**Model 3**
Total Installed Capacity [MW]	1525.60	648.82
Total / Expected Profit [MEUR]	2211.54	392.83
CVaR (10%) [MEUR]	–	191.93
Final Budget [MEUR]	2173.24	502.65
Total / Expected Revenue [MEUR]	3654.18	58.63

4.2 Deterministic vs Stochastic Investment Outcomes

The objective value of Model 1 (34.26 MEUR) represents the *minimised annual cost* under perfect information and a single-period setting. It is therefore not comparable to the multi-year, profit-maximising objectives of Models 2 and 3.

The numerical comparison in Table 2 highlights the structural differences between the two dynamic models. Model 2 achieves a total profit of 2211.54 MEUR and builds 1525.6 MW of capacity, reflecting an aggressive expansion strategy enabled by deterministic prices, no carbon exposure, and no competitive block constraints. With revenues remaining consistently high and predictable, the budget grows rapidly to 2173.24 MEUR, allowing continued reinvestment and uniform scaling across technologies.

In contrast, Model 3 operates under uncertainty in electricity prices, capture factors, and CO_2 costs. As shown in the table, total installed capacity drops to 648.82 MW and expected profit to 392.83 MEUR, which is an order of magnitude lower than in the deterministic case. The downside risk, captured by the 10% CVaR of 191.93 MEUR, demonstrates the significant spread in scenario outcomes. The optimiser therefore shifts toward a more conservative investment path, favouring technologies with stable margins across scenarios (PV and onshore wind) and avoiding diesel entirely. Although overall growth is slower, the model maintains a positive final budget of 502.65 MEUR, indicating robustness in adverse conditions.

Overall, Model 2 embodies a high-return, high-exposure strategy driven by certainty, whereas Model 3 prioritises resilience and risk mitigation through reduced capacity expansion and a renewable-heavy portfolio.

4.3 Profit Distribution and Expected Generation

Having compared the deterministic and stochastic investment outcomes, we now examine how uncertainty affects the realised financial performance and the operational behaviour of the portfolio.

The profit distribution in Model 3 reveals a wide spread in scenario outcomes, driven primarily by volatile electricity prices and CO_2 costs. While the expected profit remains positive, a substantial left tail emerges, with the 10% CVaR indicating materially lower returns in adverse scenarios.

Uncertainty also affects the operational output of technologies. In particular, the expected generation trajectories show that gas-fired generation becomes unprofitable in a number of scenarios once carbon prices rise or capture factors deteriorate. In these scenarios, the

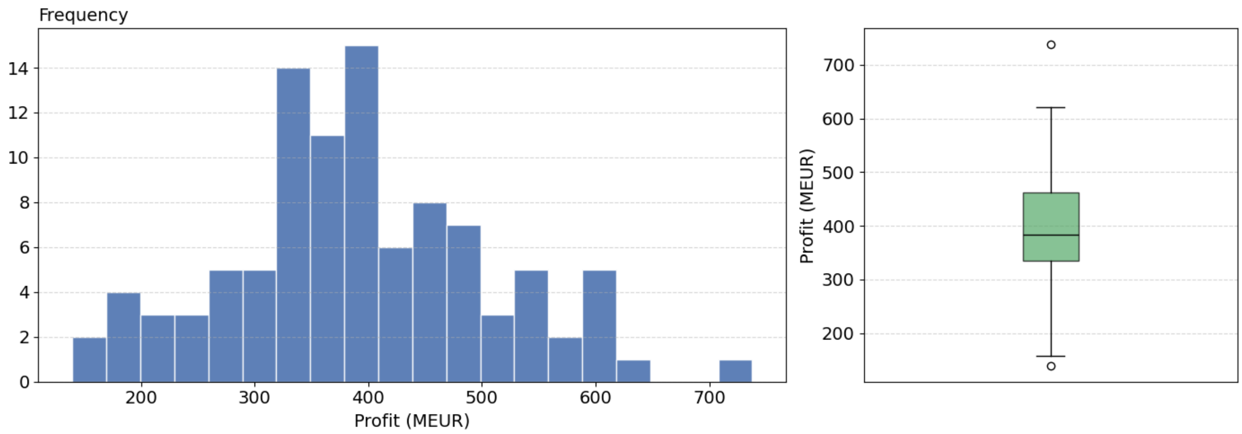

Figure 2: Profit distribution and variability across all price-capture factor scenarios in Model 3, illustrating the spread of outcomes around the expected profit and the presence of downside risk.

optimiser shuts down gas production entirely for the year, because generating at a loss would reduce the budget available for future investment. As a result, the expected annual generation profile displays drops for gas, whereas PV and onshore wind maintain stable and consistently positive output across almost all scenarios. This divergence reflects the underlying risk profiles of the technologies: renewables face mainly price volatility, while fossil assets face both price and policy-driven shocks, making their profitability more fragile under uncertainty.

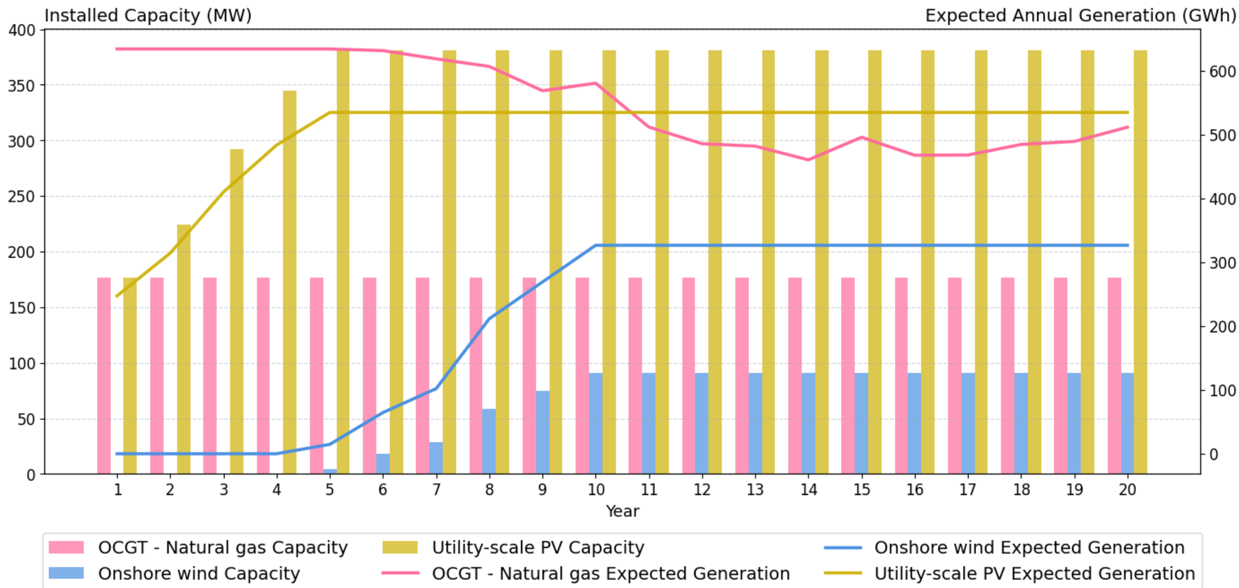

Figure 3: Installed capacity and expected annual generation over the 20-year horizon in Model 3. Bars show the evolution of built capacity, while lines indicate the corresponding expected electricity generation under stochastic market conditions.

4.4 Model Validation

During the creation of all 3 models, simple unit and sign sanity checks have been performed. Moreover, for all three models a set of synthetic extreme parameter cases (very low demand, very high budget) to verify feasibility and to confirm that standard constraints (demand balance, capacity limits, budget constraints) behaved as expected were ran. To validate the internal consistency of Model 1, a simplified, model-consistent levelised cost of electricity (LCOE) was calculated in Table 3 for all technologies, based solely on annualised capital expenditure and variable operating costs. Under an unconstrained optimisation, the model should select the technologies with the lowest LCOE, which indeed correspond to utility-scale PV, OCGT, and onshore wind. The observed plant mix therefore matches the expected cost ordering, confirming that the baseline model behaves in accordance with economic intuition. As a behavioural validation of Model 2, the optimisation with a deliberately tight initial budget was reran. Under this constraint, the optimiser correctly prioritises low-CAPEX technologies in early years and delays capital-intensive investments, confirming that the model's budget dynamics behave as economically expected. To assess internal consistency across the dynamic optimisation models 2 & 3, a cross-model validation was conducted, in which Model 3 was reduced to a setting comparable to Model 2 by setting the carbon price to zero and restricting the simulation to a single price scenario. Under these harmonised assumptions, both models exhibit similar qualitative investment and dispatch patterns, and their final budgets lie in the same range (Model 2: 4123 MEUR; Model 3: 3420 MEUR). This indicates that the additional stochastic and policy dimensions introduced in Model 3 do not conflict with the underlying economic structure of the simpler deterministic model. When the baseline carbon price trajectory is introduced (83 EUR/tCO_2 in the first year, increasing by 5 EUR/tCO_2 per year), Model 3's final budget decreases to 647 MEUR, reflecting the substantial increase in cumulative CO_2 -related costs. This exercise constitutes a structural and behavioural validation, demonstrating both (i) convergence of the extended model towards the simpler formulation under aligned inputs and (ii) an economically plausible response to carbon pricing.

4.5 Further Analysis

A sensitivity analysis can be performed ad-hoc using the created *Optimal Bidding Dashboard - Model 1 & 2*. Due to gurobi license limitations, model 3 only runs locally and not in a web-app. While model 1 can be analyzed on 4 parameters, deeper insight about the system can be derived in model 2 and 3 on six core parameters like investment data, demand structure, time horizon, etc.

5 Discussion - Limitations

The models offer many valuable insights about optimal technology mixes and investment strategies, however, a number of their limitations should be acknowledged. **Model 1** is a static, single-period cost-minimization model that does not capture multi-year dynamics, changing demand, or evolving market conditions. In fact, it assumes fixed costs, efficiencies, and lifetime, ignoring operational constraints such as hourly shipments or system reliability. Dual analysis shows low sensitivity to these constraints in the optimal plan, however, the model does not capture the full complexity of real-world operational or market interactions. **Model 2** extends the analysis to a multi-period setting in a deterministic environment, where cumulative revenue over time is maximized. However, electricity price, demand, and budgets are viewed as known inputs with no uncertainty, market shocks, or strategic competition. Similarly, simplifications have been made regarding investment timing and capacity expansion. **Model 3** involves stochastic market prices and carbon costs, and by doing so, embeds uncertainty and price-volume interactions into the model in a much more realistic way. However, this scenario-based approach may be far from perfect in capturing extreme events and correlated market shocks. Investments are still "here-and-now", and their values cannot be altered after the scenarios are realized. This stepwise market-share pricing is a simplification compared to real market behavior. Revenues, in reality, depend on complex market mechanisms and regulatory changes with price volatility, thus, actual profits may be different from the model projections. Additionally, the annual time granularity means that if production becomes economically infeasible in a given year, the model may discard the entire year's production rather than just unprofitable periods - a limitation that finer temporal modeling (e.g., quarterly, monthly or even finer resolution) could address by capturing partial shutdowns more realistically. A more accurate modeling of competition would require endogenous price formation or strategic bidding between multiple agents, which typically leads to non-linear or equilibrium-based formulations such as bi-level or Nash-Cournot models. These approaches fall outside the linear optimisation framework used here and would require substantially more data and computational resources.

The outcomes are highly sensitive to input data, such as technology costs, demand projections, electricity prices, and carbon parameters, across models. The models abstract from grid constraints, storage losses, issues of system reliability, and consumer behavior, which may overestimate the feasibility or profitability of some technology portfolios. Financial assumptions are simplified and may differ from real investment conditions. Overall, the models provide a framework for analysis but should be interpreted with these limitations in mind.

6 Deliverables & Outlook

The final deliverable is an interactive optimisation dashboard (*Optimal Bidding Dashboard - Model 1 & 2*) that allows the user to specify custom constraints, budget limits, and strategic preferences. Based on these inputs, the tool generates a tailored investment plan together with expected production, revenues, and profitability outcomes.

Future work may extend the framework by introducing a finer temporal granularity, enabling intra-year dynamics such as seasonal production patterns and short-term market fluctuations. Moreover, the model could benefit from a more detailed representation of market competition, allowing for strategic bidding behaviour, endogenous price formation, or interaction with competing investment portfolios.

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[3] International Energy Agency, "Denmark: Electricity," 2025. Accessed from IEA Country Profiles.

[4] "Eu carbon permits," 2025. Accessed from TradingEconomics: https://tradingeconomics.com/commodity/carbon.

Appendix

A Model 1 Constraints

$$
\begin{aligned}
\text{s.t.} \quad & \sum_{j \in \mathcal{J}} c_j^{\text{inv}} \cdot x_j \leq B^{init} && && (1) \\
& \sum_{j \in \mathcal{J}} E_j = E^{\text{tot}} && && (2) \\
& \sum_{j \in \mathcal{J}} y_j \geq 4 && && (3) \\
& E_j \geq 0.1 \cdot E^{\text{tot}} \cdot y_j && \forall j \in \mathcal{J} && (4) \\
& E_j \leq x_j \cdot H \cdot \eta_j && \forall j \in \mathcal{J} && (5) \\
& E_j \leq M \cdot y_j && \forall j \in \mathcal{J} && (6) \\
& x_j \geq 0, \quad E_j \geq 0, \quad y_j \in \{0,1\} && \forall j \in \mathcal{J} && (7)
\end{aligned}
$$

Constraint (1) ensures that the total investment remains within the available budget. Constraint (2) guarantees that the total annual energy production exactly meets the required demand. To promote technological diversity, constraint (3) requires the selection of at least four technologies. This process aims to better simulate a real-world energy mix scenario. Constraint (4) further ensures that each selected technology contributes a minimum of 10% to the total energy production, avoiding marginal participation. Constraint (5) enforces technical feasibility by limiting production based on installed capacity, efficiency, and annual operating hours. Constraint (6) restricts energy production to selected technologies only. Finally, constraint (7) defines the domains of the decision variables, enforcing non-negativity and binary selection.

B Model 2 Constraints

$$k_{j,0} = i_{j,0} \qquad \forall j \in \mathcal{J} \tag{1}$$
$$k_{j,t} = k_{j,t-1} + i_{j,t} \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \setminus \{0\} \tag{2}$$
$$k_{j,t} \leq \overline{K}_j \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \tag{3}$$
$$e_{j,t} \leq k_{j,t} \cdot \eta_j \cdot H \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \tag{4}$$
$$R_t = \sum_{j \in \mathcal{J}} e_{j,t} \cdot p_t \qquad \forall t \in \mathcal{T} \tag{5}$$
$$C_t^{\text{op}} = \sum_{j \in \mathcal{J}} e_{j,t} \cdot v_j \qquad \forall t \in \mathcal{T} \tag{6}$$
$$C_t^{\text{cap}} = \sum_{j \in \mathcal{J}} i_{j,t} \cdot c_j^{\text{cap}} \qquad \forall t \in \mathcal{T} \tag{7}$$
$$C_t^{\text{fix}} = \sum_{j \in \mathcal{J}} k_{j,t} \cdot f_j \qquad \forall t \in \mathcal{T} \tag{8}$$
$$B_0 = B^{\text{init}} \tag{9}$$
$$C_t^{\text{cap}} \leq B_t \qquad \forall t \in \mathcal{T} \tag{10}$$
$$B_t \geq 0 \qquad \forall t \in \mathcal{T} \tag{11}$$
$$B_{t+1} = B_t - C_t^{\text{cap}} + R_t - C_t^{\text{op}} - C_t^{\text{fix}} \qquad \forall t \in \mathcal{T} \setminus \{\max \mathcal{T}\} \tag{12}$$
$$\sum_{j \in \mathcal{J}} e_{j,t} \leq D_t \qquad \forall t \in \mathcal{T} \tag{13}$$
$$i_{j,t} \geq 0,\ k_{j,t} \geq 0,\ e_{j,t} \geq 0 \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \tag{14}$$
$$B_t,\ R_t,\ C_t^{\text{op}},\ C_t^{\text{fix}},\ C_t^{\text{cap}} \geq 0 \qquad \forall t \in \mathcal{T} \tag{15}$$

C Model 3 Constraints

$$k_{j,0} = i_{j,0} \qquad \forall j \in \mathcal{J} \tag{16}$$

$$k_{j,t} = k_{j,t-1} + i_{j,t} \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \setminus \{0\} \tag{17}$$

$$k_{j,t} \le \overline{K}_j \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \tag{18}$$

$$e_{j,t,s} \le k_{j,t}\, \eta_j\, H \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{19}$$

$$\sum_{j \in \mathcal{J}} e_{j,t,s} = q^{(1)}_{t,s} + q^{(2)}_{t,s} + q^{(3)}_{t,s} \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{20}$$

$$0 \le q^{(1)}_{t,s} \le 0.25\, D_t \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{21}$$

$$0 \le q^{(2)}_{t,s} \le 0.50\, D_t \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{22}$$

$$0 \le q^{(3)}_{t,s} \le 0.25\, D_t \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{23}$$

$$R_{t,s} = p_{t,s}\Big(q^{(1)}_{t,s} + 0.85\, q^{(2)}_{t,s} + 0.60\, q^{(3)}_{t,s}\Big) \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{24}$$

$$C^{\mathrm{op}}_{t,s} = \sum_{j \in \mathcal{J}} e_{j,t,s}\left(v_j + \tau^{\mathrm{CO_2}}_t \gamma^{\mathrm{CO_2}}_j\right) \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{25}$$

$$C^{\mathrm{cap}}_t = \sum_{j \in \mathcal{J}} i_{j,t}\, c^{\mathrm{cap}}_j \qquad \forall t \in \mathcal{T} \tag{26}$$

$$C^{\mathrm{fix}}_t = \sum_{j \in \mathcal{J}} k_{j,t}\, f_j \qquad \forall t \in \mathcal{T} \tag{27}$$

$$B_{0,s} = B^{\mathrm{init}} \qquad \forall s \in \mathcal{S} \tag{28}$$

$$C^{\mathrm{cap}}_t \le B_{t,s} \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{29}$$

$$B_{t,s} \ge 0 \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{30}$$

$$B_{t+1,s} = B_{t,s} - C^{\mathrm{cap}}_t + R_{t,s} - C^{\mathrm{op}}_{t,s} - C^{\mathrm{fix}}_t \qquad \forall t \in \mathcal{T} \setminus \{\max \mathcal{T}\},\ \forall s \in \mathcal{S} \tag{31}$$

$$\sum_{j \in \mathcal{J}} e_{j,t,s} \le D_t \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{32}$$

$$i_{j,t} \ge 0,\ k_{j,t} \ge 0 \qquad \forall j \in \mathcal{J},\ \forall t \in \mathcal{T} \tag{33}$$

$$e_{j,t,s} \ge 0,\ q^{(m)}_{t,s} \ge 0 \qquad \forall j \in \mathcal{J},\ \forall t, s,\ m = 1,2,3 \tag{34}$$

$$B_{t,s},\ R_{t,s},\ C^{\mathrm{op}}_{t,s} \ge 0 \qquad \forall t \in \mathcal{T},\ \forall s \in \mathcal{S} \tag{35}$$

$$C^{\mathrm{fix}}_t,\ C^{\mathrm{cap}}_t \ge 0 \qquad \forall t \in \mathcal{T} \tag{36}$$

Constraints (1)-(3) retain the dynamic capacity accumulation from Model 2, ensuring that installed capacity evolves consistently over time and remains within technology-specific upper bounds. Constraint (4) limits scenario-dependent production to the available capacity, accounting for efficiency and annual operating hours. Constraints (5)-(5c) introduce the tranche variables $q_{t,s}^{(m)}$ and link them to total energy sold in each period and scenario, while imposing upper bounds corresponding to 25%, 50% and 25% of total demand D_t. Constraint (6) defines the effective revenue in each period and scenario, applying the 15% and 40% discounts to the second and third tranches, respectively. Constraint (7) defines operating costs, which include both conventional variable O&M costs and an explicit carbon cost term proportional to the technology's emission factor and the carbon tax. Constraints (8) and (9) aggregate capital and fixed O&M expenditures, which remain deterministic and scenario-independent.

Constraints (10)-(13) describe the evolution of the available budget in each scenario. The initial budget is identical across scenarios, but subsequent budget states depend on the realized cash flows (revenues minus variable, fixed, and capital costs). Requiring the investment constraint (11) and non-negativity (12) to hold in every scenario enforces an investment strategy that remains financially feasible under all simulated price trajectories. Constraint (14) caps total generation by demand in each period and scenario, while constraints (15)-(18) define the domains of all decision variables.

D LCOE for all technologies - model 1

Technology	**LCOE (EUR/MWh)**
Utility-scale PV	7.75
OCGT – Natural gas	10.02
Onshore wind	10.67
Diesel engine farm	11.08
Offshore wind (fixed)	17.49
Coal power plant	21.65
Nuclear power plant	41.14

Table 3: Model-consistent LCOE calculation used for validation (annualised CAPEX + variable O&M).

E Price Volatility

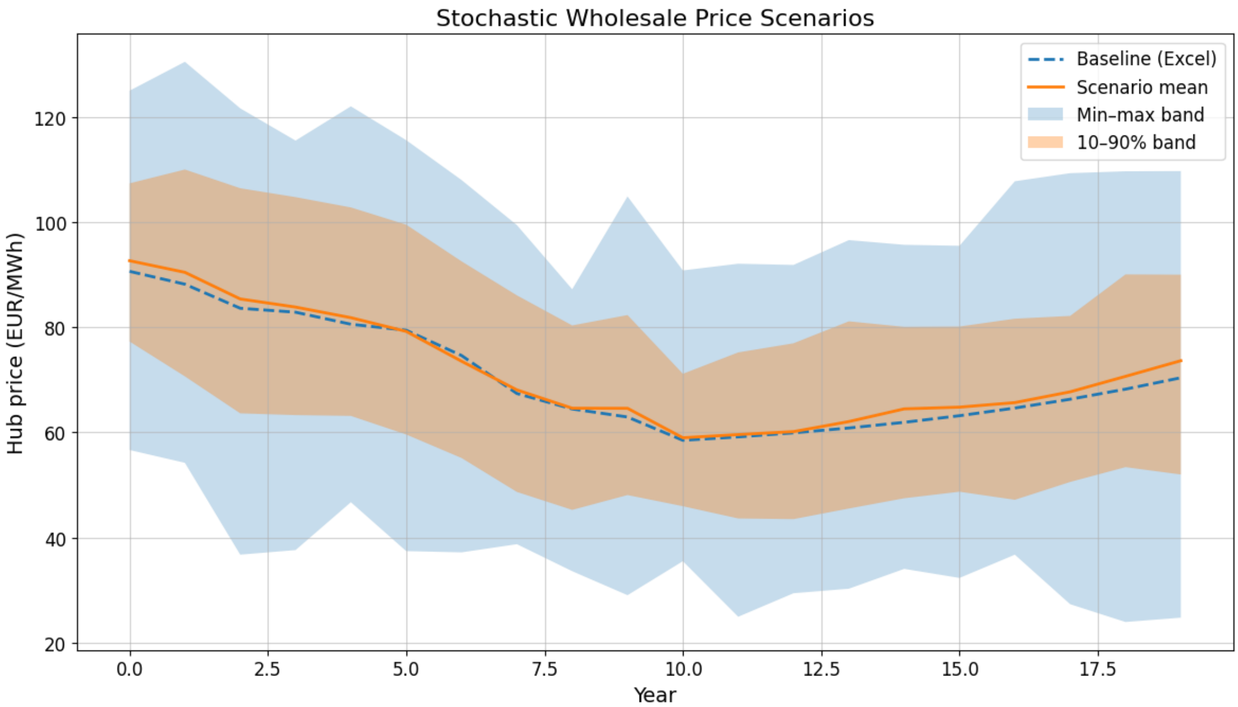
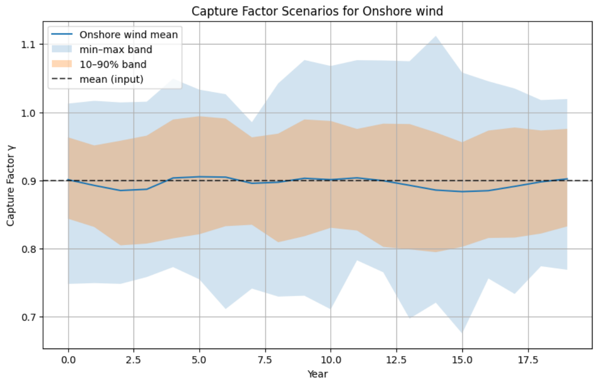
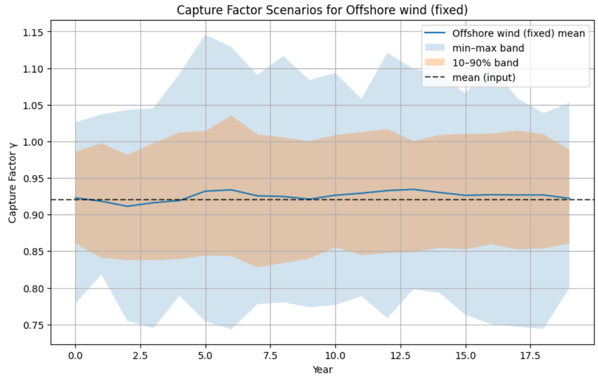


Figure 4: Wholesale price scenarios with mean path and uncertainty bands.

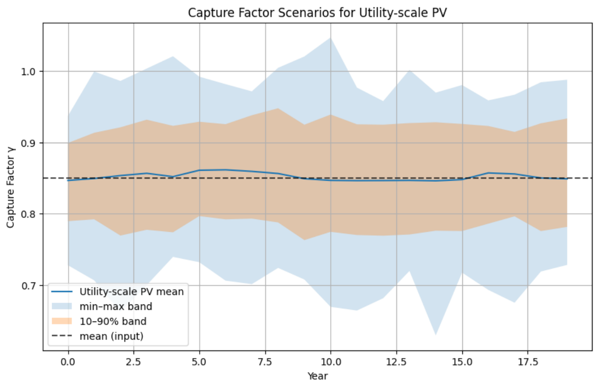
Capture rates



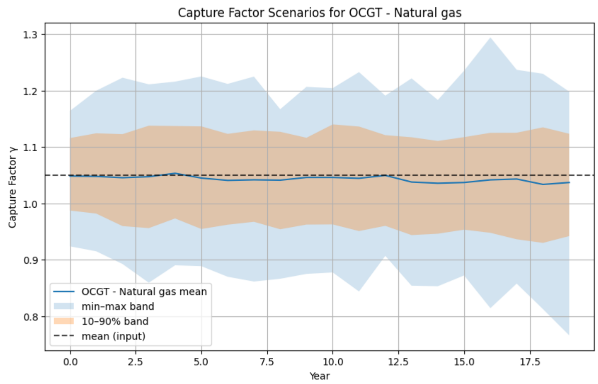
(a) Onshore wind capture factors



(b) Offshore wind capture factors



(c) PV capture factors



(d) Gas capture factors

Figure 5: Capture factor scenario distributions for the four selected technologies

F CO_2 cost

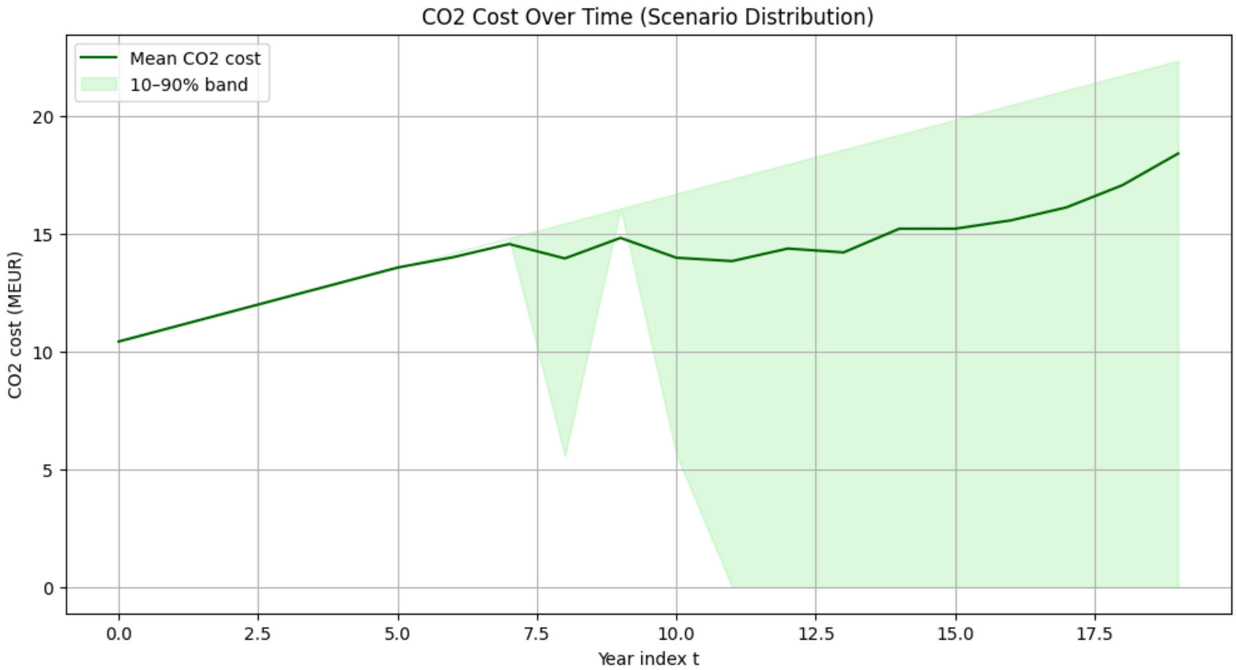


Figure 6: Generation mix and gas margins in Scenario 2, illustrating unprofitable gas operation in several years.

G Marginal gas prices and production

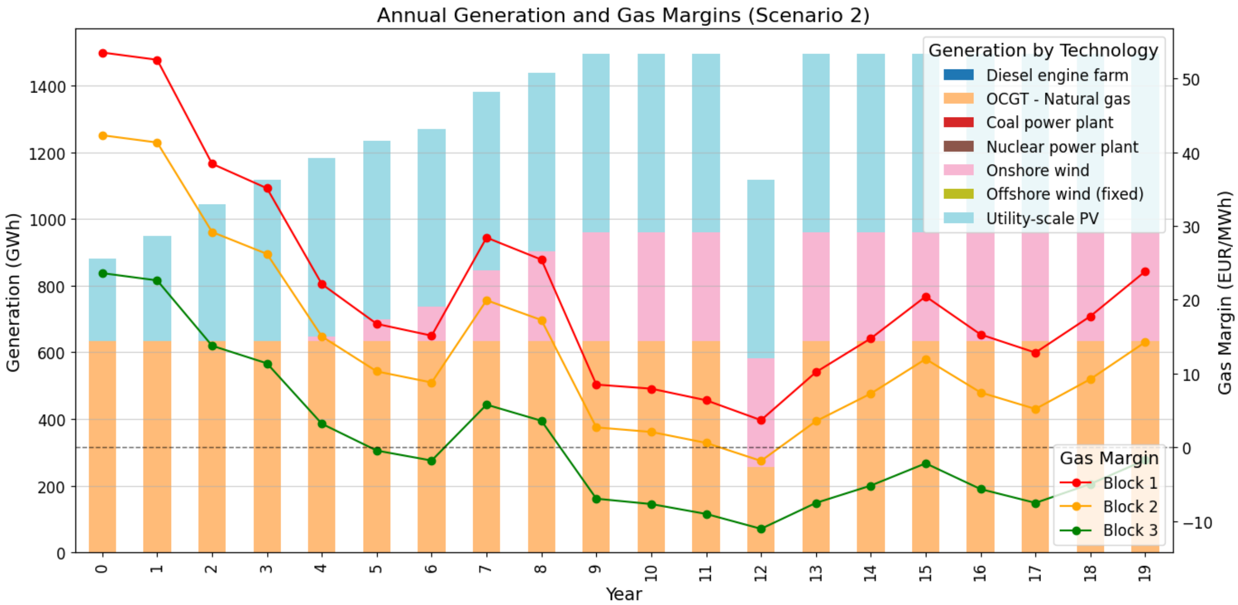


Figure 7: Generation mix and gas margins in Scenario 2, illustrating unprofitable gas operation in several years.

The Use of AI

Artificial Intelligence (AI) tools were used in the presented case study to an appropriate degree. Time-consuming tasks such as creating a preliminary document layout and supporting code debugging and visualisation were assisted by ChatGPT. All written material remains the result of personal and team work and has been critically reviewed and verified for correctness.