Karlsruher Institut für Technologie

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Abstract

The transition to a net-zero energy system requires large-scale integration of variable renewables, increasing demand for flexibility beyond short-term batteries and seasonal hydrogen. Emerging storage technologies feature cost structures that position them between these options, offering discharge durations of several hours to a few days, here referred to as mid-term storage. However, their economic feasibility depends strongly on their techno-economic parameters and evolving market dynamics. Identifying profitable and robust storage configurations under uncertain future market conditions is therefore crucial to bridge the perspectives of technology developers and investors. We employ the agent-based electricity market model PowerACE, which explicitly represents market participants as interacting decision-making agents. Using mean-reverting stochastic representations of fuel prices and renewable generation, we capture the impact of uncertainties on storage profitability from an individual investor's perspective. The analysis determines the maximum capital expenditure that still yields economically viable storage configurations across relevant combinations of techno-economic parameters. The results reveal that profitability is limited under current cost conditions, as the marginal contribution of storage capacity declines sharply with higher storage durations. At the same time, higher round-trip efficiency not only improves returns but also reduces market risk. Balancing efficiency, costs, and duration is essential for mid-term storage competitiveness, while risk-based assessments can guide robust technology and investment decisions.

Graphical Abstract

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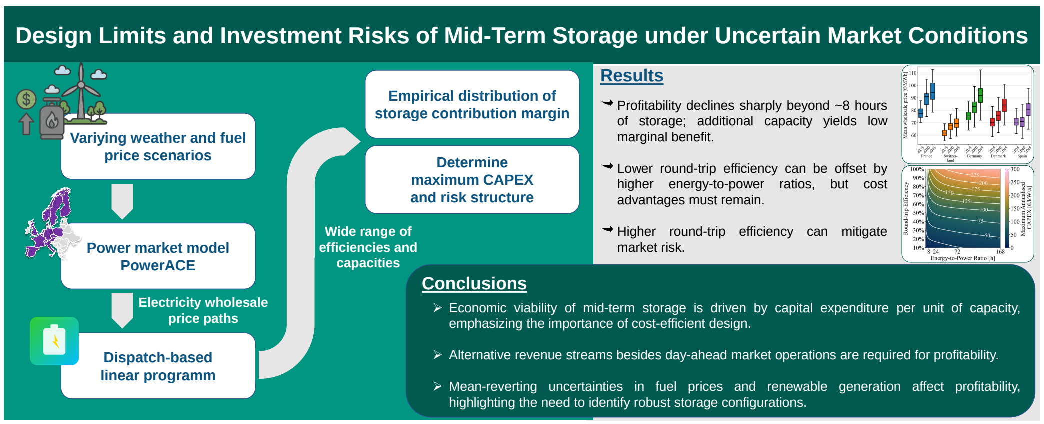

Highlights

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- Mid-term electricity storage profitability based on day-ahead wholesale prices
- Addressing uncertainties in future fuel prices and renewable generation
- Identification of maximum capital expenditure for storage configurations
- Marginal contribution of storage capacity falls with higher storage durations
- Higher round-trip efficiency improves returns and reduces risk

Design Limits and Investment Risks of Mid-Term Storage under Uncertain Market Conditions

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The transition to a net-zero energy system requires large-scale integration of variable renewables, increasing demand for flexibility beyond short-term batteries and seasonal hydrogen. Emerging storage technologies feature cost structures that position them between these options, offering discharge durations of several hours to a few days, here referred to as mid-term storage. However, their economic feasibility depends strongly on their techno-economic parameters and evolving market dynamics. Identifying profitable and robust storage configurations under uncertain future market conditions is therefore crucial to bridge the perspectives of technology developers and investors. We employ the agent-based electricity market model PowerACE, which explicitly represents market participants as interacting decision-making agents. Using mean-reverting stochastic representations of fuel prices and renewable generation, we capture the impact of uncertainties on storage profitability from an individual investor's perspective. The analysis determines the maximum capital expenditure that still yields economically viable storage configurations across relevant combinations of techno-economic parameters. The results reveal that profitability is limited under current cost conditions, as the marginal contribution of storage capacity declines sharply with higher storage durations. At the same time, higher round-trip efficiency not only improves returns but also reduces market risk. Balancing efficiency, costs, and duration is essential for mid-term storage competitiveness, while risk-based

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assessments can guide robust technology and investment decisions.

Keywords: Energy storage, Electricity markets, Investment risk, Capital expenditure, Storage technology design, Mean-reverting processes

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1. Introduction

To achieve the Paris Agreement's objective of limiting global warming to 1.5 °C above pre-industrial levels, global greenhouse gas emissions must reach net zero by mid-century [1, 2]. In the electricity sector, this led to a rapid expansion of variable renewable energy sources, which already induced profound structural changes [3, 4, 5]. Increasing renewable shares complicate the challenge of balancing supply and demand, thereby requiring enhanced system flexibility. Besides flexible conventional generation (e.g., hydrogen-ready gas turbines), additional flexibility can be provided by electricity storage, demand-side response, sector coupling, such as the integration of electrolysers, which enable load shifting and enhance grid stability [6, 7, 8]. While battery storage provides short-term flexibility by mitigating imbalances between surplus and deficit renewable generation, hydrogen-fired power plants and electrolysers are projected to offer seasonal storage solutions, complementing established resources such as hydropower [9, 10, 11]. However, both technologies face constraints: lithium-ion batteries remain costly for long storage durations and rely on critical raw materials [12, 13], while hydrogen costs and quantities are uncertain and electrolyser deployment is still in early stages [14, 15]. In this context, we refer to storage technologies designed to continuously discharge energy from several hours up to a week as mid-term storage, positioning them between battery systems and seasonal storage solutions.

This creates an opportunity for emerging storage technologies to bridge the gap between short-duration and seasonal storage solutions and provide advantageous alternatives to established options in terms of, e.g. geographical independence and material usage [12, 16, 17, 18]. Evaluating the technical design parameters of emerging energy storage technologies is therefore crucial to assess their suitability and potential. However, metrics such as the Levelized Cost of Storage (LCOS) offer only limited guidance. Being cost-based, LCOS does not adequately capture the revenue potential of storage technologies and is highly sensitive to assumptions regarding their utilisation [19, 20, 21]. To address these limitations, inverse methods are required, aimed at determining the maximum capital expenditure (CAPEX) of storage technologies across different combinations of technical design parameters that still allow economically viable investments [22].

At the same time, investors face significant uncertainties when considering emerging technologies, which strongly influence investment decisions [23, 24, 25]. Key parameters such as renewable generation profiles and short-term price dynamics are inherently stochastic and often exhibit mean reverting behaviour, fluctuating around long-term equilibrium values [26, 27, 28, 29]. Focusing on these mean reverting uncertainties enables a systematic assessment of investment risk and the identification of storage configurations that remain robust under realistic variations in market conditions. Assessing factors such as storage capacity, charging and discharging power, round-trip efficiency (RTE), and CAPEX allows technology developers to design the required system configurations, thereby creating conditions for economically viable investments in future technologies. Against this background, this work aims at:

- systematically assessing mid-term storage configurations by considering storage capacity and RTE as key technical design parameters,
- using mean reverting stochastic processes for fuel prices and renewable generation profiles to assess their impact on electricity prices and the resulting profitability of storage configurations, and
- ultimately, and as the main contribution, identifying economically viable and more robust investment options under varying future market conditions.

By considering mean reverting stochastic processes in fuel prices and renewable generation profiles within the PowerACE market model, this study quantifies how these inherent uncertainties influence the profitability of storage technologies. An inverse method is applied, systematically exploring all combinations of technical design parameters to determine the maximum CAPEX for profitability. By assessing both technical parameters and varying future market conditions, the findings underline a key gap in current research: the lack of integrated methodologies that inform storage technology design based on future investment viability.

The remainder of this paper is organised as follows. Section 2 provides a literature review and identifies the existing research gap in the assessment of techno-economic storage parameters under uncertainty arising from weather variability and fuel prices. Section 3 presents the methodological framework, including the modelling of mean reverting stochastic processes, the agent-based power market model PowerACE[1], the assessment of risk preferences, and the assumed input data underlying each of these methods. Section 4 presents the results, including an analysis of the impact of mean reverting processes on electricity price trajectories and storage profitability. Section 5 discusses the implications and limitations of the findings for technology developers and investors and Section 6 concludes with key insights and recommendations for future research.

2. Literature review and research gap

This section critically reviews the literature on energy storage assessment, focusing on cost-based and market-revenue-oriented methods. It highlights the limitations of conventional metrics, the partial advances of techno-economic approaches, and the remaining gap in linking technical design parameters with investment risk and economic viability under uncertainty. This gap motivates the integrated, risk-informed approach presented in this study.

To assess and compare energy storage technologies, the literature often relies on techno-economic metrics such as the LCOS, which has been widely applied to evaluate the cost performance of different storage options under assumed technical and economic parameters. Various studies have applied LCOS calculations to a broad range of technologies. The relative cost competitiveness of these technologies is investigated, including lithium-ion batteries, pumped hydro storage, and compressed air storage [31], with redox flow batteries and hydrogen storage additionally considered [19, 20], as well as emerging systems with gravity- or heat-based storage [32] such as Carnot batteries[2] [33]. The reviewed studies identify battery storage as most suitable for short-duration applications and hydrogen or power-to-gas systems for seasonal storage, while assessments of compressed air energy storage and pumped hydro differ, with some studies classifying them as short- and others as mid - or long-duration options.

[1] A description and overview can be found in Fraunholz (2021) [30]

[2] Carnot battery also is referred to as pumped heat energy storage or, less specifically, power-to-heat-to-power energy storage.

Further studies provide more detailed technical analyses primarily for compressed air and thermal energy storage systems, where the respective models are optimised with respect to the LCOS [34, 35, 36]. As most studies assume fixed storage durations between 6 hours - 10 hours, Tassenoy et al. [37] show that Carnot batteries maximise the net present value at a 14.5 hours charge and 21.8 hours discharge, while McTigue et al. [38] find financial potential of Carnot batteries to compete with Li-ion batteries at charge durations above 6 hours. The sensitivity analyses presented across these studies reveal that the LCOS is highly sensitive to the discharged energy volume and the electricity purchase price. Therefore, as a purely cost-based indicator, the LCOS offers only limited explanatory power for informing technology development and investment strategies. It does not adequately reflect the revenue potential that storage technologies can realise in electricity markets [21]. Consequently, additional research increasingly emphasises techno-economic modelling approaches that combine technical performance parameters with market-based revenue assessments.

These approaches enable a more comprehensive assessment of storage profitability by considering key financial indicators, including contribution margins, the net present value or the internal rate of return. Taponen et al. [39] evaluate mid-term energy storage options based on day-ahead and intraday market prices for Finland in 2023. They find that, while day-ahead trading alone is not economically viable, intraday operations can improve profitability. With a focus on the investor perspective, Spodniak et al. [40] investigate key factors influencing the economic viability of large-scale, centralised electricity storage in the day-ahead markets in Germany, the UK and Scandinavia during the period 2006-2016 for different Energy-to-Power (EtP) ratios. The find that for the markets and time-frame considered, the marginal increase in contribution margins decreases quickly as the EtP ratio is increased, where the highest specific contributions margins (per MWh of storage capacity) are observed for an EtP ratio of 1. By analysing lithium-ion battery performance in day-ahead markets in 22 countries (2016–2022), Komorowska et al. [41] find that batteries yield a negative net present value under their capital costs assumptions for 2022. Poli et al. [42] came to the same conclusion for redox-flow batteries, evaluating them in the Italian market. Cetegen et al. [43] find that a liquid air energy storage in the Texas electricity market with a 16 hours charge and 8 hours discharge can cover both CAPEX and operational expenditure, whereas Vecchi et al. [44] show in a UK case how simultaneous participation in reserve markets can further increase revenues. Similarly, Nitsch et al. [45] simulate the German day-ahead and automatic frequency restoration reserves markets to evaluate revenue potentials of battery storages using an agent-based electricity market model. For a 2030 market with high shares of renewable energies, they find that compared to 2019, the economic potential will increase and so will the importance of the day-ahead market.

Nevertheless, even within more market-based modelling frameworks, most studies still rely on predefined cost assumptions and focus on specific storage technologies. While such analyses can indicate whether a given technology may be economically viable under certain conditions, they do not provide insights into how storage systems should be designed or which techno-economic parameter combinations (i.e., investment cost, storage capacity, or round-trip efficiency) would enable profitability. Consequently, there is a need for approaches that explicitly link technical design parameters to economic feasibility. Esser et al. [22] develop a multi-objective inverse modelling approach that links technical design parameters directly to generation expansion planning. They demonstrate their approach for Carnot batteries using a model setup that includes five European countries in the target year 2050 under full decarbonisation conditions, and find that the maximum allowable CAPEX at which these systems remain endogenously deployed is low, at around 140 €/kW (12 €/kW/a). However, higher EtP ratios effectively improves allowable CAPEX. For the same target year under a full decarbonisation scenario, Nitsch et al. [46] combine generation expansion with market modelling to show that Carnot batteries become economical at annualised CAPEX levels of 25–27 €/kW/a for EtP ratios of 7–8 h and 3.7–35.8 GW of installed capacity. Sorknæs et al. [47] investigate the system cost reduction potential of Carnot batteries in a 100 % renewable Danish energy system for the target year 2045. They identify an economic threshold of 60–66 €/MWh for discharging costs, corresponding to annualised CAPEX of roughly 165 €/kW/a. By integrating Carnot batteries exogenously into the German electricity market for the years 2030–2040, Stelzer et al. [48] conclude that higher EtP ratios of Carnot batteries lead to lower profitability, as the additional revenue does not fully compensate for the increased costs associated with the larger EtP ratio. Together, these studies advance storage analysis toward integrated generation expansion and competitiveness perspectives, revealing thresholds of emerging storage technologies to enter and sustain market relevance. However, these techno-economic assessments do not capture the full extent of inherent risks and uncertainties in future energy market conditions, including fluctuating electricity prices and renewable generation variability.

Studies that combine investment risk and uncertainty with storage valuation tend to move away from identifying maximum cost thresholds or applying inverse modelling approaches. Instead, they focus again on predefined technology configurations and parameter sets, thereby limiting insights into how design choices influence economic feasibility under uncertainty. Geske et al. [49] use a Markov decision model to optimise storage capacity under uncertain residual load (from demand and wind/solar variability), finding that these uncertainties increase effective storage costs by 27 % from 4.1 €/kWh to the perfect-foresight value of 5.6 €/kWh. In addition, Hammann et al. [50] apply a real options approach to evaluate the option value of adiabatic compressed air energy storage, where uncertainties such as varying natural gas prices lead to a high option value. Bakke et al. [25] have analysed the profitability of lithium-ion battery investments under variable spot and balancing prices, showing that high uncertainty in future battery costs leads investors to postpone investment decisions until additional information becomes available. While such approaches provide valuable insights into investment risk, they fall short of linking the underlying techno-economic parameters to the resulting investment feasibility.

Therefore, to bridge technical design optimisation with risk-informed investment assessment, we assess mid-term storage options by considering storage capacity and round-trip efficiency as key technical design parameters. By using mean reverting stochastic processes in fuel prices and renewable generation profiles to evaluate their impact on electricity prices and storage profitability, we identify economically viable investment options that remain robust under varying future market conditions.

3. Methods

To evaluate the performance and investment risk of mid-term storage technologies, we explicitly consider uncertainty in the electricity system. Variability in renewable generation and electricity demand profiles is represented by the set $\mathcal{I} = \{1, ..., I\}$ of weather scenarios, each weighted according to its probability of occurrence, while fuel price uncertainty is represented by the set $\mathcal{J} = \{1, ..., J\}$ of fuel price scenarios and modelled using an Ornstein-Uhlenbeck (OU) process to capture its mean reverting properties. The resulting $N = I \cdot J$ scenarios, combining weather scenario $i \in \mathcal{I}$ and fuel price path $j \in \mathcal{J}$ as scenario (i, j), serve as input for the agent-based power market model PowerACE to generate N electricity price paths. In the model, a fixed energy system trajectory is assumed, i.e., there is no endogenous generation expansion or any structural change to the power plant fleet across scenarios. These price paths are subsequently used in a linear storage-dispatch program outside of the PowerACE simulation. In this step, the storage operation is optimised with respect to the maximisation of the contribution margin for each individual price path, determining the economically optimal charging and discharging schedule for the respective storage configuration. The resulting optimal dispatch decisions are then used to compute the distribution of contribution margins $\hat{F}_{\pi_k}$ for each parameter combination $k \in \mathcal{K} = 1, \ldots, K$, providing a systematic risk assessment for investors and allowing the identification of storage configurations that remain economically robust under both weather and fuel price uncertainty. The described methodological framework is illustrated in Figure 1.

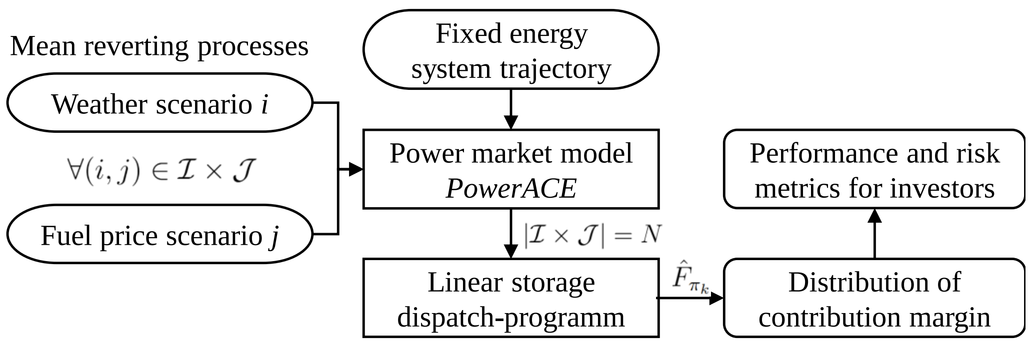


Figure 1: Overview of the methodological process from data input to investment risk assessment.

3.1. Representation of mean reverting processes

3.1.1. Weather scenarios

To account for uncertainties associated with the future patterns of generation and demand profiles, 36 distinct weather scenarios were considered. A weather scenario represents a full year of hourly data, including 8760 hourly capacity factors for renewable generation and corresponding electricity demand profiles. The scenarios were taken from the European Resource Adequacy Assessment (ERAA) Executive Report 2024 [51], which provides datasets for renewable generation and demand profiles under varying future weather and climate conditions. To quantify the probability of occurrence for a given weather scenario $i \in \mathcal{I}$, we apply a weighted aggregation approach that accounts for spatial, technological and temporal heterogeneity. The probability weight w_i^w of scenario i is defined as:

$$w_i^w = \sum_{a=1}^{A} \sum_{c=1}^{C} \sum_{m=1}^{M} w_{a,c}^{\text{comp}} \cdot w_{a,c,m}^{\text{bin}} \tag{1}$$

where:

- $w_{a,c}^{\text{comp}}$ represents the relative share of contribution of component c in area a with respect to the total contribution across all areas. Here, c refers to the installed capacity of solar power, onshore wind or offshore wind power or the total demand in area a.

- $w_{a,c,m}^{\text{bin}}$ denotes the fraction of weather scenarios in area a, for component c and month m that fall within a predefined bin. The bins are defined based on the standard deviation of the corresponding time series of a component. Specifically, for each month, the mean of the time series (e.g., hourly capacity factors) is calculated for each scenario. Then, the overall mean across all scenarios for that month is determined. The deviation of each scenario's monthly mean from the overall monthly mean is computed and assigned to a bin, such that all scenarios within the same bin are assigned the same probability. Bins are defined such that the probability of each bin is given by the fraction of scenarios that fall within it. Deviations are categorized into bins corresponding to the ranges between $-2, -1, 0, 1, 2$ standard deviations, with any values below or above these limits assigned to the outermost bins.

By summing over all areas, components, and months, we obtain a weight for each weather scenario for a given year. A more detailed mathematical formulation of the approach can be found in Appendix B.2. For the components, we use the same values from the fixed energy pathway trajectory described in Section 3.2 and presented in Appendix A.1. The resulting weather scenario weights are presented in Appendix A.2.

3.1.2. Fuel price scenarios

Modelling of fuel prices often requires stochastic processes. A widely applied framework is the OU process [52, 53, 54, 55], which is defined by the stochastic differential equation

$$dX_t = \theta(\mu - X_t)\,dt + \sigma\,dW_t \tag{2}$$

where μ denotes the long-term equilibrium level, θ is the speed of mean reversion, σ the volatility parameter, and W_t a standard Wiener process [56, 57]. Here, t represents time steps, corresponding to the daily fuel prices. The process is particularly suitable for commodities in energy markets, since empirical price dynamics often revert to a long-term average while still exhibiting short-term noise [58, 59]. Our processes follow the Ten-Year Network Development Plan (TYNDP) scenarios over the period from 2030 to 2050, using initial values X_0 for 2030 from the TYNDP 2024 [60] and setting the long-term mean μ according to the projected 2050 fuel and CO_2 prices. mean reversion speed and volatility of the OU process are estimated from historical time series using a discrete-time approximation [61, 62, 63]. Specifically, an autoregressive regression of order one is performed on the observed price differences, from which the OU parameters θ and σ are derived: the slope of the regression corresponds to $-\theta\Delta t$ and the standard deviation of the residuals provides σ. As historical data, front-month price data from the respective exchanges over 2023 and 2024 are used for calibration. The analysis considers gas, oil, and hard coal, while hydrogen is included under the assumption that its price dynamics will evolve in a manner similar to natural gas. This assumption is justified by the expectation that emerging hydrogen markets remain closely tied to gas price developments [64, 65, 66]. Since carbon prices are intrinsically linked to fossil fuel consumption, a joint modelling approach is required. Therefore, for each fuel price series, the corresponding emission factor [60] is combined with the CO_2 price, such that the resulting time series already incorporates the cost of associated carbon emissions. To account for the dependence of fuel prices, we introduce correlations using a Cholesky decomposition of the empirical covariance matrix. The univariate process in Equation 2 is then extended to a multivariate process, after discretisation:

$$X_{t+\Delta t} = X_t + \theta \cdot (\mu - X_t)\,\Delta t + Lz\sqrt{\Delta t}, \tag{3}$$

where z is a vector of standard normal draws and L is the lower-triangular matrix obtained from the Cholesky decomposition of the empirical covariance matrix Σ, such that $\Sigma = LL^\top$. The parameters X_0, μ, θ and σ of the multivariate OU process and the empirical covariance matrix is given in Appendix A.3.

We simulate 1,000 fuel price paths of the multivariate OU process. To incorporate such a large set of trajectories directly into the analysis would, however, be computationally prohibitive. Therefore, a clustering procedure is applied to reduce the dataset. First, the simulated paths are reduced to their two principal components via principal component analysis. Subsequently, the resulting components are grouped into ten clusters using K-Means clustering. For each cluster, the time series closest to the cluster centroid (i.e., minimising the Euclidean distance) is selected as the representative fuel price path, denoted by $j \in \mathcal{J}$, and assigned a weight w_j^f proportional to the fraction of total paths contained in that cluster. The resulting ten representative fuel price paths with their weights are presented in Appendix A.4. All prices are reported in nominal € for each year, using inflation rates from the World Economic Outlook 2024 [67].

3.2. Power market model PowerACE: electricity price path imulation

The mean reverting processes described in Section 3.1 are used to simulate varying day-ahead electricity price paths for the years 2035, 2040 and 2045. By assuming a fixed energy pathway trajectory, the variability in weather years and fuel prices allows for representing the uncertainties in these underlying mean reverting processes for future day-ahead electricity price developments.

The simulations are carried out using the agent-based power market model PowerACE. PowerACE is a simulation framework based on individual market participants, designed for the analysis of European electricity markets. Its primary purpose is to enable long-term assessments of the day-ahead market. Depending on the input data resolution, the model simulates 8760 hours of a year across extended time horizons. Over the past years, PowerACE has been applied in a variety of research contexts, such as studies about electricity prices [68], capacity remuneration mechanisms [69], the analysis of electric vehicle market impacts [70] and for assessing the role of risk aversion in capacity expansion planning [24].

Within the model, market participants are equipped with internal decision-making strategies that define their individual objectives, such as the maximisation of profits. These participants continuously interact with their environment and, on each simulated day, submit demand or supply bids according to their respective strategies. The day-ahead market outcome is then determined by a welfare-maximising market-clearing algorithm, which accounts

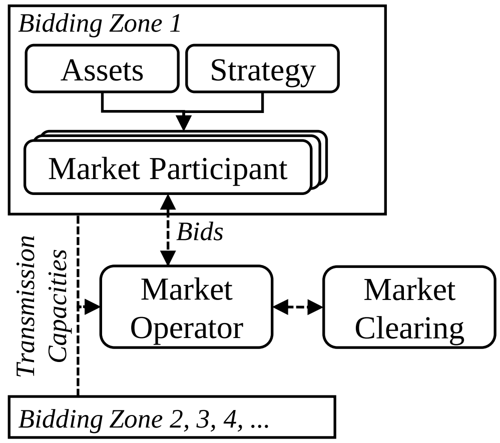


Figure 2: Simplified overview of the power market model PowerACE.

for all submitted bids as well as the available cross-border transmission capacities. A comprehensive and authoritative description of the structure and individual modules of the PowerACE model can be found in [30]. Since then, the model has undergone minor refinements. Figure 2 provides a simplified representation of the modelling approach used in this study. Consistent with the assumptions above, the energy system trajectory of the TYNDP 2024 Global Ambition Scenario is applied. In the energy system trajectory, the installed capacity is expanded by additional gas turbine power plants to fulfil the required system reliability in each bidding zone. The simulations cover 16 bidding zones, each with its respective day-ahead wholesale market prices. By combining ten representative fuel price trajectories with 36 weather scenarios, a total of $N = 360$ day-ahead price paths are generated for each year and each bidding zone.

3.3. Linear storage dispatch-programm

A commonly studied application of energy storage is electricity price arbitrage, where electricity is purchased at low prices and sold at higher prices. Assuming that the storage system is small enough that its charging and discharging do not affect market prices, analyses of this price-taker scenario often assume perfect optimisation of the device when faced with known electricity prices.

The simulated day-ahead wholesale electricity price paths obtained from the PowerACE model are used as input for such a simplified storage dispatch optimisation problem, with the objective of maximising the contribution margin given the technical design parameters such as storage capacity, charging and discharging power, and RTE.

Let T denote the number of time steps in the considered price path. The decision variables are the charging power P_t^{ch}, discharging power P_t^{dis}, and state-of-charge SOC_t at each time step $t \in \{1, \ldots, T\}$.
The optimisation problem is formulated as follows:

$$\max_{P_t^{\mathrm{ch}}, P_t^{\mathrm{dis}}, SOC_t} \quad \sum_{t=1}^{T} \left(-P_t^{\mathrm{ch}} \cdot p_t + P_t^{\mathrm{dis}} \cdot p_t \right) \tag{4}$$

$$\begin{aligned} \text{s.t.} \quad & SOC_{t+1} = SOC_t \\ & \quad + \eta^{\mathrm{ch}} P_t^{\mathrm{ch}} \\ & \quad - \frac{1}{\eta^{\mathrm{dis}}} P_t^{\mathrm{dis}} \quad \forall t = 1, \ldots, T \end{aligned} \tag{5}$$

$$0 \leq SOC_t \leq C \quad \forall t \tag{6}$$

$$0 \leq P_t^{\mathrm{ch}} \leq P^{\mathrm{ch,max}} \quad \forall t \tag{7}$$

$$0 \leq P_t^{\mathrm{dis}} \leq P^{\mathrm{dis,max}} \quad \forall t \tag{8}$$

$$SOC_1 = 0.5 \cdot C \tag{9}$$

Here, p_t denotes the simulated day-ahead electricity price at time t, C is the storage capacity, $P^{\mathrm{ch,max}}$ and $P^{\mathrm{dis,max}}$ are the maximum charging and discharging powers, and η^{ch} and η^{dis} are the charging and discharging efficiencies. The initial state-of-charge is set to 50 % of the storage capacity, with self-discharge as well as variable operation and maintenance costs neglected.

The problem is solved sequentially across multiple price paths, but simultaneously for different storage parameter combinations, with a warm-start procedure applied to accelerate convergence across price paths. In this study, the discharge and charge powers are fixed to 1 MW, efficiencies are varied from 10 % to 100 % in in 1-percentage-point increments, and 168 different storage capacities are considered, resulting in a total of $91 \cdot 168 \cdot 360 = 5{,}503{,}680$ linear program evaluations for a single bidding zone and year with $T = 8760$. Using this approach, solving the optimisation for all scenarios for one year and bidding zone takes on average approximately 440 minutes on an AMD Ryzen Threadripper 3970X 32-core processor using the simplex algorithm.

The objective value of the optimisation can be interpreted as the annual contribution margin per MW generated by the storage in a given year, which can be used to cover the equivalent annualised investment and fixed operation and maintenance costs. Conducted independently of PowerACE, this approach facilitates the systematic evaluation of diverse system configurations and allows for the adjustment of key parameters, such as the EtP ratio, while simultaneously determining the maximum CAPEX that ensures economically viable operation for a 1 MW system with a given RTE and capacity.

3.4. Performance and risk metrics for investors

Investment decisions under uncertainty can be systematically evaluated using the empirical distribution of profitability across different scenarios. In the context of this study, each simulated day-ahead price path is assigned a weight corresponding to its probability $w^p_{i,j}$, defined as the product of the weight of the weather scenario w^w_i and the fuel price trajectory w^f_j, which in turn induces a probability distribution for the annual contribution margin, derived in Section 3.3, which determines the maximum economically viable CAPEX. According to [24], the empirical distribution function and the corresponding empirical cumulative distribution function of the contribution margin for a given storage configuration can then be used to derive various decision metrics, allowing consideration of both expected profitability and risk exposure.

Formally, let $\pi_{k,(i,j)}$ denote the contribution margin of parameter combination $k \in \mathcal{K}$ under the price path scenario defined by weather year i and fuel price path j, with associated scenario probability $w^p_{i,j}$. The expected contribution margin $\mathbb{E}(\pi_k)$ of a parameter combination k is then defined as the weighted average over all scenarios:

$$\mathbb{E}(\pi_k) = \sum_i \sum_j w^p_{i,j}\, \pi_{k,(i,j)}. \tag{10}$$

To account for risk aversion in investment decisions, risk measures are applied to the empirical distribution $\hat{F}_{\pi_k}$. Based on the empirical cumulative distribution function, a well-established and widely used risk measure is the value at risk (VaR_α), which indicates the threshold of the contribution margin that will be achieved or exceeded with a given confidence level. Specifically, the

VaR_α at confidence level α is given by

$$\mathrm{VaR}_\alpha(\pi_k) = \max\Big\{q : \Pr\big(\pi_{k,(i,j)} < q\big) \leq 1-\alpha\Big\},$$
$$\forall \alpha \in (0,1). \tag{11}$$

and the conditional value at risk (CVaR_α), which is a coherent and widely used risk measure, is defined as the contribution margin conditional on falling below the VaR_α:

$$\mathrm{CVaR}_\alpha(\pi_k) = \mathbb{E}\Big[\pi_{k,(i,j)} \mid \pi_{k,(i,j)} \leq \mathrm{VaR}_\alpha(\pi_k)\Big],$$
$$\forall \alpha \in (0,1). \tag{12}$$

To jointly account for expected profitability and risk, a linear combination of the expected value and the CVaR is applied, following the approach of Fraunholz et al. [24]:

$$\pi_k^* = (1-\lambda)\,\mathbb{E}(\pi_k) + \lambda\,\mathrm{CVaR}_\alpha(\pi_k),$$
$$\lambda \in [0,1],\ \alpha \in (0,1), \tag{13}$$

where λ represents the investor's degree of risk aversion, with $\lambda = 0$ corresponding to risk-neutral and $\lambda = 1$ to highly risk-averse preferences. Following this approach, π_k^* provides a single metric that quantifies the maximum contribution margin achievable for each storage parameter combination, and therefore the maximum CAPEX under which economically viable operation is maintained. To determine the relative competitiveness of each storage configuration compared to another, the deviation of the maximum annualized CAPEX is calculated as

$$\Delta\pi_k^{\mathrm{ref}} = \pi_k^* - \pi^{\mathrm{ref}} \tag{14}$$

where π^{ref} denotes the maximum annualized CAPEX of the reference configuration for the same λ. A positive value of $\Delta\pi_k^{\mathrm{ref}}$ indicates that configuration k can sustain higher annualized CAPEX than the reference system while maintaining economic viability, whereas a negative value indicates lower allowable CAPEX. Additionally, for $\lambda = 0$ and $\lambda = 1$, the percentage change of the maximum annualized CAPEX can be expressed as

$$\Delta\pi_k^{\mathrm{risk}} = \frac{\pi_k^*(\lambda=0) - \pi_k^*(\lambda=1)}{\pi_k^*(\lambda=0)} \times 100\%, \tag{15}$$

where

$$\pi_k^*(\lambda = 0) = \mathbb{E}(\pi_k),$$
$$\pi_k^*(\lambda = 1) = \mathrm{CVaR}_\alpha(\pi_k),$$

which can be interpreted as the risk premium of a highly risk-averse investor relative to a risk-neutral investor.

Equations 13, 14 and 15 quantify the economic competitiveness and impact of risk preferences on the maximum achievable contribution margin and the corresponding maximum annualized CAPEX for each storage configuration, taking into account both expected performance and downside risk.

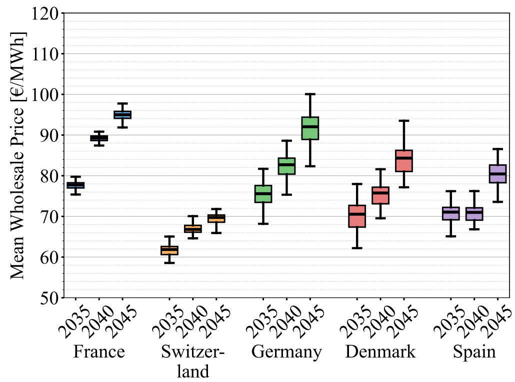
4. Results

4.1. Comparison of electricity price paths

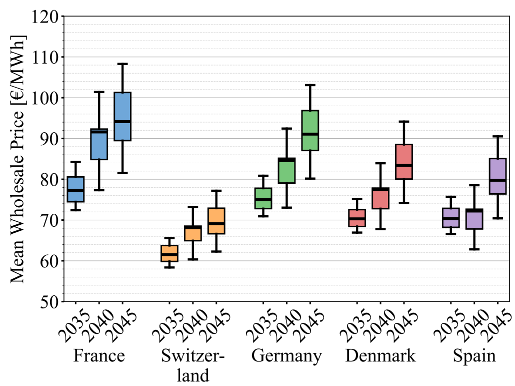
In Figure 3a, the distribution of mean prices is shown for the years 2035, 2040, and 2045[3] across different European countries under varying weather scenarios, i.e. wind and solar generation profiles. Figure 3b illustrates the corresponding distributions under varying fuel price assumptions[4]. The scenarios capture structurally diverse energy systems: Germany is characterised by high renewable penetration combined with increasing demand, France remains strongly reliant on nuclear power, Denmark is dominated by wind generation, Spain benefits from abundant solar resources, and Switzerland reflects its characteristic hydro-based system, while also being strongly influenced by neighbouring countries. The comparison between weather-year and fuel price scenarios reveals distinct sensitivities across the analysed countries. Due to its reliance on nuclear power, France shows only minor variation across different weather years, but is strongly affected by changes in fuel prices. Switzerland exhibits a similar pattern: weather-year variations have little impact, while fuel price assumptions significantly influence the mean price distribution. In Germany, fuel price assumptions dominate the distribution of mean prices, reflecting the role of flexible thermal generation (e.g., gas turbines or hydrogen-based plants), while variations across weather years also have a significant impact. Denmark has a large wind generation

[3]The exogenous energy system trajectory and the corresponding demand for each year can be found in Appendix A.1.

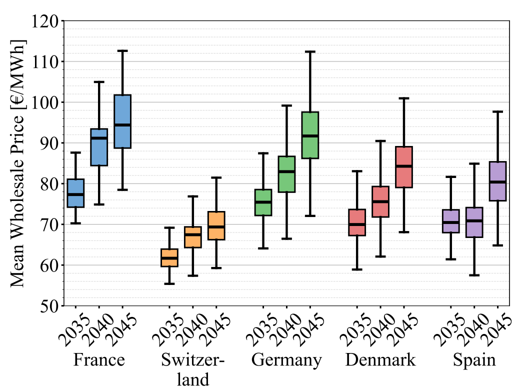
[4]The fuel price scenarios and their variability can be found in Appendix A.4.



(a) Distribution across varying weather scenarios, with fuel price scenarios averaged per weather scenario.



(b) Distribution across varying fuel price scenarios, with weather scenarios averaged per fuel price scenario.



(c) Distribution across all weather and fuel price scenarios.

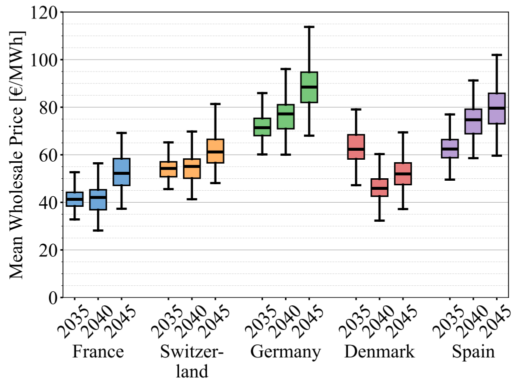
Figure 3: Boxplots of mean wholesale prices for different European countries across scenarios.

capacity, which allows it to cover a substantial share of its electricity demand from domestic wind resources. However, its system is strongly influenced by Germany, resulting in similar sensitivities to changing conditions. In Spain's solar-dominated system, solar variability has a relatively minor effect on the price distribution, whereas fluctuations in fuel prices of flexible thermal power plants drive changes in mean values.

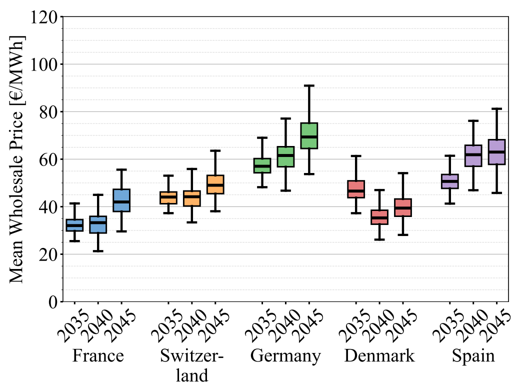
Figure 3c presents the distribution of mean prices when both weather year and fuel price variations are considered simultaneously. The combination of these two sources of uncertainty introduces differences in all analysed countries. Comparing across years, it becomes apparent that the variance of the mean price distributions tends to increase in 2040 and 2045. The impact of fuel price variations is relatively high compared to weather scenario variations, as the mean prices diverge further due to the dynamics of the OU process (cf. Appendix A.4). Moreover, in systems where weather scenario variations have a significant impact (e.g., Germany), the overall spread of mean price distributions becomes notably larger compared to countries where weather sensitivity is low (e.g., France). Consequently, the combination of sensitivity to both weather scenarios and fuel price variations drives the overall variation to the greatest extent.

For storage profitability, price spreads are particularly relevant. Therefore, in addition to the mean prices, Figure 4 presents the distribution of the averages of the second-, fourth-, and eighth-highest daily price spreads[5]. As the fourth-highest daily spread remains relatively close to the second-highest, an increase in storage capacity could be beneficial within this range. In contrast, the eighth-highest spread is considerably lower, implying that increasing capacity or using low-efficiency storage would yield only limited contribution margins when exploiting these spreads. Comparing countries, price spreads are consistently highest in Germany, indicating favourable conditions for storage profitability. Spain also exhibits relatively large spreads, suggesting similarly favourable opportunities. In contrast, France, dominated by nuclear generation, and Denmark, with a high share of wind power, exhibit lower spreads, implying less attractive conditions for storage deployment. The absolute variation in average spreads across different fuel price and weather scenarios is highest for the 2-hour spreads, while it decreases for the 8-hour spreads (cf. Germany 2045: 49.21 €/MWh vs. 19.05 €/MWh).

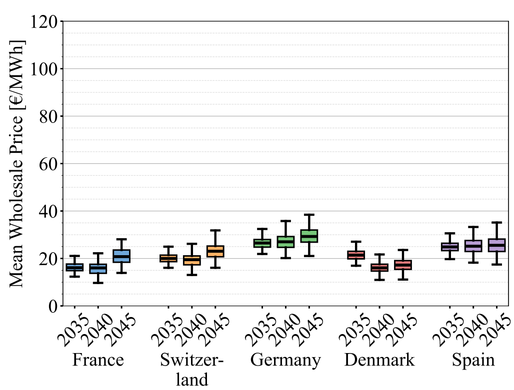
[5] The calculation of daily spreads is detailed in Section Appendix B.1.



(a) Distribution of the daily mean of the second-highest spread.



(b) Distribution of the daily mean of the fourth-highest spread.



(c) Distribution of the daily mean of the eighth-highest spread.

Figure 4: Boxplots of mean wholesale price spreads for different European countries across scenarios.

Accordingly, the potential exploitation of these spreads by storage systems results in more consistent contribution margins between scenarios.

4.2. Competitiveness of different storage parameter combinations

In the following subsections, when we refer to a risk-neutral or risk-averse investor, we consider the contribution margin π^*, as defined in Equation 13. A risk-neutral investor corresponds to $\lambda = 0$, while a risk-averse investor corresponds to $\lambda = 1$. Accordingly, for a risk-neutral investor, the figures depict the expected value of the contribution margin, whereas for a risk-averse investor, the CVaR_α of the contribution margin is shown. We assume that the maximum annualised CAPEX shown in the following subsections equals the contribution margin π^*_k for a year that can be achieved with the respective combination of storage parameters k. Since the values represent the maximum allowable annualised costs to ensure profitability, any fixed operation and maintenance costs, if considered, would need to be deducted accordingly to obtain the maximum admissible CAPEX.

As described in Section 3.3, discharge and charge powers are fixed to 1 MW, while storage capacities are varied between 1 MWh and 168 MWh. The round-trip efficiency (RTE) is modelled via input efficiency, such that all storage capacities are expressed in electrical terms. Accordingly, the storage capacity can be described by the Energy-to-Power (EtP) ratio, which denotes the discharge duration, i.e., the time a storage system can continuously release energy at its rated power from full charge to full discharge in hours.

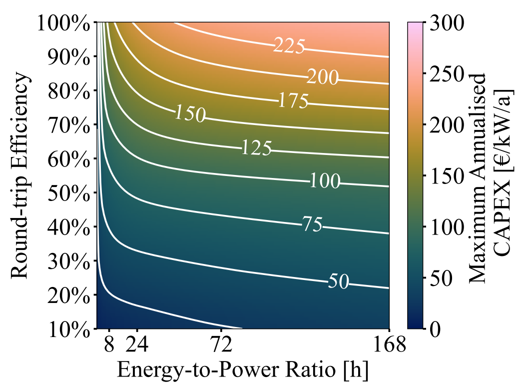


Figure 5: Maximum annualised CAPEX π^* (cf. Equation 13) in Germany (2035) for a risk-neutral investor ($\lambda = 0$) .

Figure 5 shows the maximum annualised CAPEX π^* for Germany in 2035 required to achieve an annuity of zero, as a function of EtP ratio and RTE, assuming a risk-neutral investor. The contour lines in Figure 5 represent equal maximum annualised CAPEX values, which allow to identify combinations of EtP ratio and RTE that are economically equivalent. For example, a technology with lower RTE can achieve comparable economic performance if the EtP ratio is sufficiently increased. It can be observed that, particularly for low EtP ratios, an increase in RTE yields comparatively little economic benefit, as lines of equal maximum annualised CAPEX are predominantly vertical in this region. In contrast, an increase in EtP ratio proves to be more advantageous. With higher EtP ratios, this pattern changes: the contour lines shift towards a more horizontal orientation. Consequently, further increases in the EtP ratio become less beneficial, while improvements in RTE gain relative importance. From this, it becomes evident that the marginal value of additional capacity declines rapidly and remains at low levels from around 8 hours of storage duration onward, depending on the RTE, as this turning point appears to shift to higher EtP ratios as RTE increases. The same qualitative observations apply to the years 2040 and 2045, as well as to the other analysed countries. While the absolute levels of the maximum annualised CAPEX differ due to variations in price spreads across different years and countries, the qualitative relationships between EtP ratio and RTE remain unchanged. The corresponding figures are provided in Appendix A.5 and Appendix A.6.

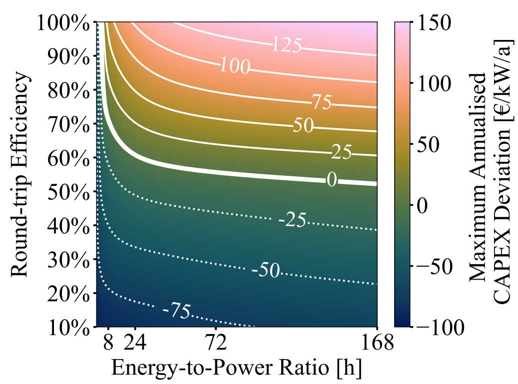


Figure 6: Maximum annualised CAPEX deviation $\Delta\pi_k^{\mathrm{ref}}$ according to Equation 14 for $\lambda = 0$ in Germany (2035) required to achieve the same annuity relative to a 4 hour EtP ratio and 92 % RTE storage system with a contribution margin π^{ref} of 101.04 €/kW/a.

Figure 6 shows a similar graph for Germany in 2035 for a risk-neutral investor. The maximum annualized CAPEX deviation $\Delta\pi_k^{\mathrm{ref}}$ is shown relative storage system representing a lithium-ion battery. The resulting deviation shows how much more or less annualised CAPEX is allowed for each storage configuration compared to the lithium-ion battery to achieve the same annuity. Therefore, the contour along the zero line represents combinations of parameters that yield the same annuity as the reference lithium-ion battery, if the annualised CAPEX between them are equal. It can similarly be inferred that higher (lower) techno-economic parameters allow for correspondingly greater (smaller) CAPEX deviations to be competitive. This relationship exhibits the same quantitative trend as the maximum allowable CAPEX shown in Figure 5.

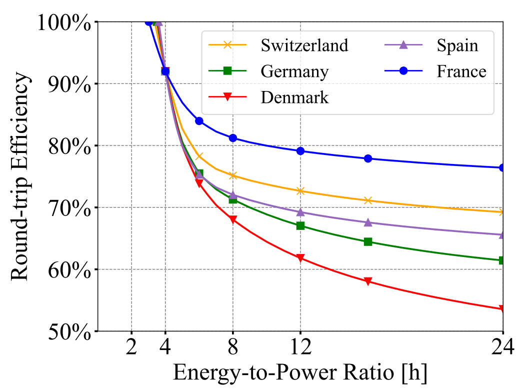


Figure 7: Extracted zero-contour lines (cf. Figure 6) for different countries averaged over the years 2035, 2040, 2045, showing combinations of RTE and EtP that yield the same annuity as the reference 4 hour lithium-ion battery system.

For Figure 7, contours along the zero line are extracted for different countries. At a low EtP ratio, the curves show little variation. They decline sharply, meaning that an increase in the EtP ratio allows for a large reduction in RTE while maintaining the same profitability. The differences emerge at the points where the curves transition from a rather vertical to a more horizontal profile. This occurs at different RTE values. For EtP ratios up to 8 hours, increasing the EtP ratio can still allow substantial reductions in RTE, averaging 18.5 % across all countries when moving from a 4 hour to an 8 hour EtP ratio. In most countries and years, these benefits level off around this point. Beyond 8 hours, further increases in the EtP ratio yield diminishing gains, averaging 8.3 % across all countries when moving from an

8 hour to a 24 hour EtP ratio. However, in some cases, such as Germany, appreciable reductions persist for EtP ratios up to 24 hours. Notably, the location of this transition varies across countries and years: in the cases of Switzerland and France, the transition starts for higher RTE, resulting in a more rapid diminishing benefit of higher EtP ratios, while in Germany, Spain, and Denmark, the transition starts at a lower RTE, indicating that lower a RTE benefits from higher EtP ratios for competitiveness. The comparison of this reference lithium-ion system indicates that competitiveness can be maintained even at lower efficiencies, provided that the EtP ratio is sufficiently high. As can be inferred from Figure 5, this observation can be generalised to energy storage technologies more broadly, suggesting that economic competitiveness at lower efficiencies can be achieved through a higher EtP ratio. However, this requires that the marginal costs of additional capacity remain low enough to keep the overall CAPEX at a level comparable to the lithium-ion reference. At the same time, total CAPEX must be low enough to ensure that the achievable contribution margin still results in a profitable investment.

4.3. Investors risk

Figure 8 shows the percentage deviation in maximum allowed CAPEX between a risk-neutral and a risk-averse investor in Germany for 2035, calculated as $\Delta\pi_k^{\text{risk}}$, with risk aversion incorporated via CVaR_α at $\alpha = 95\%$. The percentage change can be interpreted as the risk premium of a highly risk-averse investor relative to a risk-neutral investor. It can be observed that for higher RTE values, an initial increase in the EtP ratio can still reduce risk, but the effect diminishes as the EtP ratio continues to rise. For values around 50 % RTE, the effect is already relatively flat from the beginning, whereas for lower RTE values, an initial increase in the EtP ratio reduces risk at first, but later on the risk starts to increase again. By varying the RTE, it can be observed that for lower EtP ratios, the effect on the risk premium is rather inconsistent. However, for higher EtP ratios, it becomes evident that an increase in RTE leads to the strongest reduction in the risk premium, especially when compared to the influence of the EtP ratio itself.

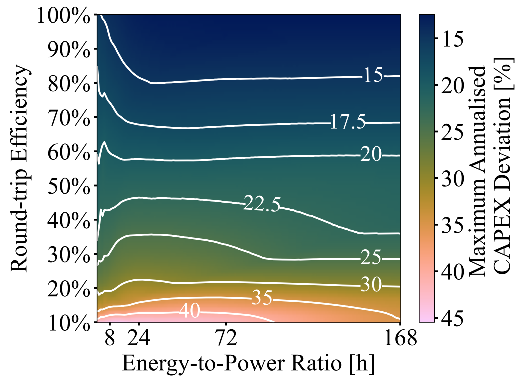
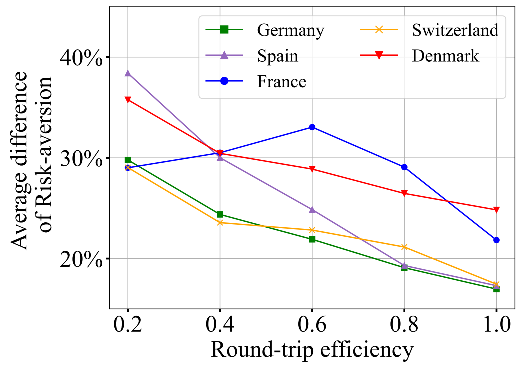
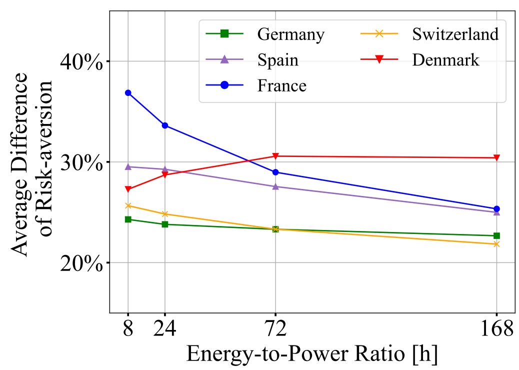


Figure 8: Percentage change in maximum annualised CAPEX $\Delta\pi_k^{\mathrm{risk}}$ (cf. Equation 15) for a risk-averse investor ($\lambda = 1$) relative to a risk-neutral investor ($\lambda = 0$) for Germany in 2035.

Figure 9a illustrates the change in the risk premium $\Delta\pi_k^{\mathrm{risk}}$ with increasing RTE, averaged over all years for each country and across all EtP ratios corresponding to that RTE. It can be observed that, for all countries except France, the risk premium decreases as RTE increases, although the rate of decrease varies between countries. Figure 9b shows a similar analysis, but with increasing EtP ratio. Here, notable differences between countries emerge: while Germany exhibits hardly any effect, France experiences a substantial decrease in the risk premium as EtP increases. In contrast, Denmark's risk premium increases with higher EtP ratios. For risk-averse investors, higher RTE can thus be desirable. Although the magnitude of this effect clearly depends on the country-specific market conditions, it can reduce the risk premium in some cases, making investments relatively less risky. Consequently, technologies that achieve elevated RTE may be particularly attractive to conservative investors, as they mitigate perceived uncertainties and stabilise expected returns.



(a) Average change in the risk premium with increasing RTE for each country, averaged over all years and all EtP ratios corresponding to that RTE.



(b) Average change in the risk premium with increasing EtP ratio for each country, averaged over all years and across all RTE values corresponding to that EtP.

Figure 9: Average risk premium change $\Delta\pi_k^{\text{risk}}$ (cf. Equation 15) for a risk-averse investor ($\lambda = 1$) relative to a risk-neutral investor ($\lambda = 0$). Lower values indicate a smaller difference between a risk-averse and risk-neutral investor, reflecting more robust contribution margins

5. Discussion

The primary contribution of this paper lies in assessing storage profitability from an investor's perspective, while simultaneously providing valuable insights for the design of storage technologies. In particular, the findings highlight which technical characteristics are most critical for achieving stable revenues under uncertain future market conditions. This, in turn, provides an important foundation for developing storage technologies that can offer economically viable investment options and align technical design choices with the requirements of future electricity markets.

5.1. Implications for the design of emerging storage technologies

One of the central findings of this work concerns the role of emerging storage technologies in bridging the mid-term storage gap between short-duration and seasonal storage systems. Whether this mid-term segment can be effectively established is primarily determined by the underlying CAPEX structure, i.e., by the cost of adding additional storage capacity. As shown in Figure 5, for increasing EtP ratios beyond 24h, the contour lines exhibit an almost constant slope. This indicates minor changes of the maximum CAPEX for a given efficiency with increasing EtP ratios, as the marginal contribution margin decreases rapidly with increasing storage capacity, a finding, which is in line with [40]. On the other hand, for a constant EtP ratio, increasing RTE lead to significant improvements in maximum allowable CAPEX, demonstrating how improvements in RTE strongly enhance the economic margin for storage technologies, aligning with the findings of Sioshansi et al. [71]. This implies that if seasonal storage technologies are already economically viable considering their total CAPEX, they will remain profitable in the mid-term range. For short-duration technologies, however, CAPEX levels must already be sufficiently low to realise economically viable systems. If the marginal CAPEX per additional unit of capacity is too high, these technologies cannot profitably extend into the mid-term range. Hence, the emergence of a mid-term storage segment in the market is less subject to the EtP ratio itself, but a function of cost structure. The CAPEX characteristics of technologies aimed at serving this segment must enable them to outperform short-duration storage systems at higher storage durations while remaining competitive against seasonal solutions. This outperforming effect, where total CAPEX of mid-term systems becomes lower than that of short-duration systems, must occur at sufficiently small capacities to prevent seasonal storage from dominating the same range through more favourable cost scaling. For technology development and design, this implies that minimising CAPEX per unit of capacity should be a key design objective, as it enables the technology to reach economically viable operation at relatively low EtP ratios. Figure 6 further illustrates that technologies with lower RTE can match the performance of lithium-ion batteries by increasing their EtP ratio, but this requires careful optimisation of component sizing and material utilisation to keep the specific CAPEX per unit of energy low.

The RTE represents an additional design lever, highlighting the importance of improving conversion efficiency to enhance the overall competitiveness of mid-term storage technologies compared to short- and long-duration systems. Enhancing these design aspects can thus enable technology developers to offer attractive and competitive incentives for investors. Nevertheless, the relevance of these design implications depends strongly on the underlying market context and temporal framework. For instance, Esser et al. [22] report contrasting results, suggesting different design priorities for emerging storage technologies. For the example of Carnot batteries, they find that an increase in the EtP ratio more efficiently increases the maximum allowable CAPEX than the RTE. Thus, for the design of emerging technologies, they suggest favouring an increase in the EtP ratio over the RTE. We explain these disparities by the fundamental differences between the underlying modelling approaches. As opposed to the agent-based PowerACE model, their energy systems optimisation represents a central planner's long-term perspective on the system's capacity expansion under perfect foresight. In their model, an optimal system is determined for predefined input parameters so that a higher EtP can help reduce system costs (one of the optimisation objectives). This is in contrast to the agent-based approach used in this paper, where a change in the EtP mainly affects the storage technology's own profitability. Moreover, in the optimisation model by Esser et al., system marginal costs (often interpreted as a proxy for prices in linear models) are determined endogenously. In this work, however, prices are obtained from running the PowerACE model for a predetermined power system, which is not necessarily in its optimal state. These prices are then assumed as exogenous inputs to the contribution margin maximisation of the energy storage. Furthermore, from an agent's perspective, short-term market mechanisms can optimally be utilised for low EtP ratios (cf. Figure 4), fully exploiting daily price arbitrage for profit maximisation. Thereby, the RTE directly impacts the losses per cycle and the revenues from each arbitrage action.

For technology design, these insights highlight the importance of considering both modelling perspectives to support robust product development and guide design strategies for emerging storage technologies. In particular, technology developers should account for two key requirements. First, designs must address system-level needs from a central-planner perspective, ensuring adequate energy provision, for example through higher EtP ratios. Second, technologies must also be economically viable from an individual view, meaning that storage systems should exhibit performance characteristics that support positive investment returns, such as a sufficiently high round-trip efficiency.

5.2. Implications for investors

Based on the implications for technology design, several conclusions can be drawn for potential investors. Given Table 1, which presents the annualised CAPEX for various storage technologies, it becomes evident that the maximum CAPEX required to reach economic break-even, as illustrated in Figures 5, lies far below the investment levels associated with storage technologies indicated in the Danish Energy Agency Technology Data Report [72]. I.e., the marginal cost of additional capacity exceeds the marginal contribution margin attainable through market operations, implying that further capacity expansion does not yield a positive annuity. Moreover, as shown in Table 1, lithium-ion batteries[6] become more expensive in annuity terms than alternative technologies beyond a certain EtP threshold. However, at these thresholds, the marginal contribution margins are already significantly reduced, such that further investment is not economically justified. A comparison of Table 1 with Figure 5 demonstrates that the points at which the annuity would reach parity are already located beyond the economically attractive region for additional capacity investments. Consequently, mid-term storage investments are not profitable under these scenario assumptions and market conditions if relying solely on arbitrage opportunities in the day-ahead market. This suggests that for storage technologies to become viable, additional revenue streams or market mechanisms (e.g., capacity payments or ancillary services) will be required, or a behind-the-meter application may be more favourable. Similar conclusions have been made by Taponen et al. [39] and Drury et al. [73].

[6] Under the assumptions results in Table 1, lithium-ion batteries would not constitute a profitable investment. This contrasts with their currently (2025) high attractiveness and grid-connection requests in Germany, which is largely driven by revenues from multiple value streams across different markets, whereas our analysis considers arbitrage income from a single wholesale market only.

Table 1: Maximum annualised CAPEX for Germany in 2035 (risk-neutral) and annualised CAPEX derived from the reference with discount factor of 7 % for different technologies in € /kW/a, considering different EtP ratios. If the maximum allowed annualised CAPEX exceeds the option's annualised CAPEX, the corresponding RTE/EtP combination is considered a profitable investment under the given assumptions.

	RTE	EtP		
		4h	8h	24h
Lithium-ion battery	92 %			
Maximum allowed annualised CAPEX		101.04	143.04	182.97
Annualised CAPEX [a]		138.30	265.80	775.79
Vanadium redox flow battery	80 %			
Maximum allowed annualised CAPEX		88.34	119.48	152.09
Annualised CAPEX [a]		195.01	353.13	985.60
Compressed air energy storage	70 %			
Maximum allowed annualised CAPEX		76.48	98.64	125.30
Annualised CAPEX [a]		181.85	246.32	504.23
Carnot battery (low RTE)	30 %			
Maximum allowed annualised CAPEX		31.78	37.96	45.52
Annualised CAPEX [b]		165.37	292.59	801.43
Carnot battery (high RTE)	73 %			
Maximum allowed annualised CAPEX		80.01	104.88	133.44
Annualised CAPEX [b]		155.61	245.56	605.36

All CAPEX values in nominal €
[a] [72]
[b] [74]

From a risk perspective, technologies with a higher RTE exhibit reduced sensitivity to investors' risk preferences, resulting in more stable investment incentives under uncertainty, as illustrated in Figure 9a. In contrast, an increase in the EtP ratio itself only marginally affects the robustness of investment attractiveness under risk considerations for most countries (cf. Figure 9b). Beyond an EtP of 72 hours, further increases in the EtP ratio do not significantly alter the risk structure. This can be explained by the following reasoning. A high RTE enables the storage system to profitably exploit even smaller price spreads and, thus, is less dependent on large spreads. Conversely, a higher EtP ratio primarily increases the number, but not the magnitude, of spreads that can be utilised. These additional spreads must be large enough to ensure profitability given the corresponding RTE. Moreover, as a higher EtP ratio allows for the exploitation of a larger number of price spreads, the variation among these additional spreads decreases (cf. Figure 4), resulting in less variation of the contribution margin between scenarios. Thus, RTE acts as a double-positive driver: it enhances absolute profitability while simultaneously minimising the exposure to market uncertainties from mean reverting processes. RTE can therefore not only be interpreted as an economic advantage but also as a risk-mitigating factor in energy storage investments. From a financial perspective, this allows for reducing the risk premium or discount rate adjustment that investors apply to uncertain revenue streams. This highlights RTE as a central parameter in evaluating the profitability and risk profile of storage investments.

5.3. Limitations and outlook

This study relies on scenario data from the TYNDP 2024 Global Ambition Scenario [60] as well as weather years from the ERAA 2024 framework [51]. Therefore, our results represent estimates of potential future developments, based on current trends and technologies, but are naturally subject to uncertainty. Future technological innovations or alternative development pathways could lead to different outcomes. Additionally, as is often done in the literature, fuel prices are modelled and assumed to exhibit mean reverting behaviour. Since there are arguments both for and against this behaviour[7], it remains uncertain whether past patterns will persist in the future. Furthermore, the PowerACE simulation model used in this study focuses exclusively on the day-ahead spot market for electricity. Although this market plays a central role in price formation and trading decisions, other markets, such as intraday trading, capacity markets, and balancing services, may offer additional economically relevant opportunities for storage systems. The multiplicity of markets and revenue streams and the consideration thereof in market models is an important area of future research (for a discussion, see [76]). As the consideration of these markets is beyond the scope of this study, the results may be regarded as a conservative estimate. Another aspect of future electricity markets that is not considered here, is the impact of sector

[7]For a discussion, see Pindyck (1999) [75]

coupling on price formation through the opportunity costs of a cross-sectoral demand, which can become price-setting [77].

Concerning the linear energy storage optimisation model, it is important to acknowledge that it operates under the assumption of perfect foresight over an entire year. As it runs outside of the PowerACE simulation and uses only the resulting price paths, this approach does not take into account the potential feedback effects on market outcomes. The results should therefore be interpreted as indicative of potential first-mover advantages or market entry opportunities under static market conditions. With regard to the techno-economic parameters of storage systems, it is important to note that neglecting fixed and variable costs, as well as technical characteristics such as ramp rates or self-discharge losses, can have a significant impact on the robustness and accuracy of the results. In addition, this study primarily focuses on uncertainties arising from mean reverting processes for fuel prices and renewable generation time series. It should be emphasised that additional sources of uncertainty, for example, those related to future expansion pathways of generation or storage infrastructure, could also have a significant impact on investment outcomes. Incorporating these factors might alter both the timing and scale of optimal investment decisions, highlighting the inherent complexity and unpredictability of long-term energy system planning.

Future research could improve the assessment of storage investment opportunities by modelling endogenous investments that directly compete with other technologies, rather than assuming static market conditions. Additionally, incorporating a broader range of uncertainties, such as path-dependency from uncertain capacity expansion, would provide a more comprehensive view of potential investment risks and timing. Finally, examining behind-the-meter applications and other alternative use cases, as well as exogenous investment incentives such as capacity remuneration mechanisms, could reveal additional pathways for achieving profitable mid-term storage investments.

6. Conclusion

Focusing on electricity storage in future energy systems, we assess the impact of storage capacity and round-trip efficiency on investment profitability under uncertainties in fuel prices and weather conditions. By integrating mean reverting stochastic processes for fuel prices and renewable generation profiles within the PowerACE market model, we systematically evaluate how these inherent uncertainties affect the economic performance of storage technologies. Using an inverse approach, we explore all combinations of technical design parameters, identifying the maximum capital expenditure that allows storage configurations to remain profitable under future system conditions.

From our assessment, we identify the following design limits and investment risk insights regarding the profitability of mid-term storage technologies:

- The economic viability of technologies designed to bridge mid-term storage gaps depends primarily on their cost structure, specifically, the capital expenditure per additional unit of capacity. Technologies with lower round-trip efficiency can remain competitive if they achieve sufficiently high energy-to-power ratios while maintaining low specific capital expenditure, highlighting the critical interplay between efficiency, storage duration, and investment costs in the design of mid-term storage solutions.

- Under the examined market conditions, mid-term storage investments are not economically viable, as the marginal contribution of additional capacity is outweighed by the associated costs. To achieve financial feasibility for these technologies, alternative revenue streams are required, or additional use cases could be explored. Potential options include participation in ancillary service markets, the utilization of political instruments such as capacity remuneration mechanisms, or other applications, for example, behind-the-meter deployment.

- mean reverting uncertainties in fuel prices and renewable generation profiles significantly influence the profitability of storage technologies, making the identification of robust configurations essential. Efficiency plays a dual role by both increasing absolute profitability and reducing market risks. Higher round-trip efficiency decreases sensitivity to investor risk aversion, thereby stabilising the economic attractiveness of storage under uncertainty. In contrast, the energy-to-power ratio has a comparatively smaller impact on risk profiles. Beyond approximately 72 hours of storage duration, further increases provide no additional benefits in terms of risk mitigation.

Overall, our results enable the identification of storage configurations that remain economically viable and robust across a range of realistic system conditions, providing actionable guidance for technology developers and investors when designing storage systems for future electricity markets.

CRediT authorship contribution statement

Jonathan Stelzer: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Katharina Esser**: Writing – review & editing. **Thorsten Weiskopf**: Software, Writing – review and editing. **Armin Ardone**: Conceptualization. **Valentin Bertsch**: Writing – review & editing, Funding acquisition, Project administration, Supervision. **Wolf Fichtner**: Funding acquisition, Project administration, Supervision.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeeplL and ChatGPT in order to avoid grammatical and spelling errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Research Data

The data for electricity price paths and resulting contribution margins is provided and can be accessed via Zenodo: 10.5281/zenodo.17791669.

Data Statement

Except for the electricity price paths and the resulting contribution margins, the data used in this study cannot be shared publicly due to restrictions. However, they are available from the sources cited in the paper.

Appendix A. Input assumptions and additional results

Appendix A.1. Capacities of energy system trajectory

Table A.2: Capacities and total demand in the fixed energy system path for each country.

	2035	2040	2045	Unit
Germany				
Total electricity demand	892.84	1021.25	1145.83	[TWh]
Natural gas turbine	79.41	67.16	33.58	[GW]
Hydrogen turbine	17.13	25.44	45.01	[GW]
Wind	192.27	225.75	243.92	[GW]
Solar	299.47	383.95	420.17	[GW]
Other renewable / thermal	13.24	9.76	8.2	[GW]
Reservoir	0.81	0.81	0.81	[GW]
Lithium-ion batteries	50.17	78.53	99.80	[GW]
Pumped Hydro Storage	9.37	10.73	10.73	[GW]
Electric vehicles	26.23	48.74	48.74	[GW]
Demand Side Response	20.10	20.94	21.67	[GW]
Electrolyser	22.71	36.79	60.24	[GW]
France				
Total electricity demand	559.57	636.56	701.80	[TWh]
Natural gas turbine	6.5	6.02	4,91	[GW]
Hydrogen turbine	0.78	1.56	4,28	[GW]
Nuclear	64.50	66.00	58.06	[GW]
Wind	67.98	87.37	105.87	[GW]
Solar	93.7	122.57	158.08	[GW]
Other renewable / thermal	16.01	16.01	16.01	[GW]
Reservoir	9.84	9.84	9.84	[GW]
Lithium-ion batteries	3.35	6.66	10.23	[GW]
Pumped Hydro Storage	4.24	4.84	5.46	[GW]
Electric vehicles	22.43	34.91	41.09	[GW]
Demand Side Response	6.50	6.50	6.50	[GW]
Electrolyser	4.18	10.42	19.80	[GW]

	2035	2040	2045	Unit
Switzerland				
Total electricity demand	65.55	72.78	73.09	[TWh]
Wind	0.73	1.15	1.69	[GW]
Solar	9.77	10.1	11.71	[GW]
Other renewable / thermal	4.71	4.93	5.21	[GW]
Reservoir	8.73	8.93	9.05	[GW]
Lithium-ion batteries	0.67	1.11	1.56	[GW]
Pumped Hydro Storage	5.19	6.02	6.14	[GW]
Electrolyser	0.26	0.26	0.26	[GW]
Denmark				
Total electricity demand	104.48	131.64	150.75	[TWh]
Natural gas turbine	1.52	1.11	1.11	[GW]
Hard coal	1.24	1.17	1.17	[GW]
Wind	30.8	37.8	44.55	[GW]
Solar	21.71	22.32	23.38	[GW]
Other renewable / thermal	0.75	0.75	0.75	[GW]
Lithium-ion batteries	0.53	0.53	0.55	[GW]
Electric vehicles	0.55	0.91	1.93	[GW]
Electrolyser	19.60	29.12	35.07	[GW]
Spain				
Total electricity demand	403.38	474.05	501.07	[TWh]
Natural gas turbine	20.51	20.51	17.71	[GW]
Wind	79.66	85.83	91.99	[GW]
Solar	103.09	134.73	144.74	[GW]
Other renewable / thermal	5.15	5.15	5.15	[GW]
Reservoir	11.41	11.41	11.41	[GW]
Lithium-ion batteries	4.60	7.4	8.3	[GW]
Pumped Hydro Storage	11.13	11.73	12.73	[GW]
Electric vehicles	15.29	24.06	28.35	[GW]
Demand Side Response	2.70	3.50	3.75	[GW]
Electrolyser	29.00	32.75	39.15	[GW]

Appendix A.2. Weather scenario weights

Table A.3: Weather scenario weights for ERAA 2024 weather scenario capacity factor profiles

Scenario	2035	2040	2045
WS1	0.025655	0.028575	0.028580
WS2	0.027332	0.028470	0.028476
WS3	0.028940	0.030704	0.030719
WS4	0.027652	0.027183	0.027151
WS5	0.031591	0.028482	0.028501
WS6	0.030094	0.027443	0.027461
WS7	0.033703	0.029007	0.028981
WS8	0.028069	0.028446	0.028392
WS9	0.027828	0.029552	0.029479
WS10	0.031980	0.030164	0.030222
WS11	0.028304	0.026438	0.026453
WS12	0.032032	0.029264	0.029239
WS13	0.030445	0.028291	0.028295
WS14	0.028848	0.028318	0.028255
WS15	0.018540	0.024816	0.024843
WS16	0.020470	0.026941	0.026933

Scenario	2035	2040	2045
WS17	0.028312	0.025594	0.025608
WS18	0.027452	0.027076	0.027079
WS19	0.017281	0.023767	0.023791
WS20	0.030023	0.029914	0.029914
WS21	0.032243	0.028905	0.028915
WS22	0.023606	0.025715	0.025765
WS23	0.029310	0.028105	0.028108
WS24	0.023566	0.024748	0.024810
WS25	0.028857	0.027420	0.027428
WS26	0.027353	0.027433	0.027451
WS27	0.026537	0.026931	0.026914
WS28	0.029302	0.029757	0.029767
WS29	0.030190	0.027404	0.027374
WS30	0.029525	0.030467	0.030469
WS31	0.018973	0.021817	0.021843
WS32	0.028389	0.026216	0.026162
WS33	0.029915	0.027962	0.028012
WS34	0.031944	0.031927	0.031882
WS35	0.026139	0.027577	0.027563
WS36	0.029597	0.029172	0.029167

Appendix A.3. Empirical covariance matrix of historical fuel prices and parameters of the multivariate OU process

Table A.4: Parameters of the multivariate OU process.

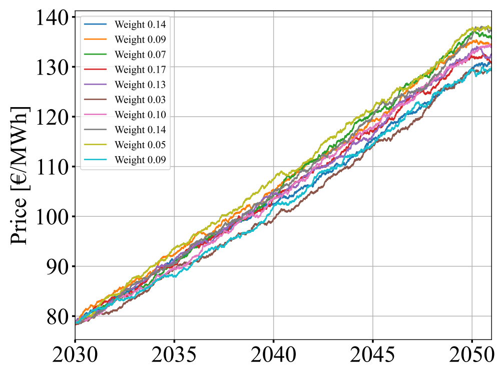
Parameter	Hard coal	Natural gas	Crude Oil	Hydrogen
X_0 [a]	78.55	56.48	57.76	78.50
μ [a]	134.54	95.65	119.36	112.20
θ	0.04	0.03	0.03	0.03
σ	0.60	1.29	0.50	1.29

[a] in nominal €

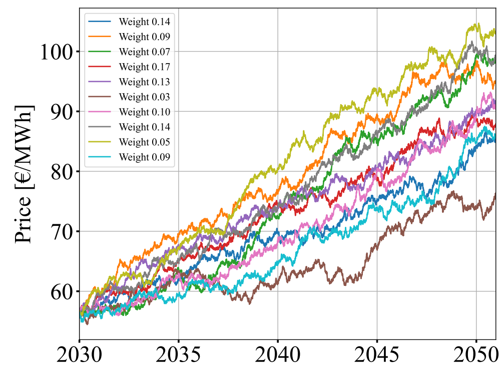
Table A.5: Covariance matrix for multivariate OU process

	Crude Oil	Natural Gas	Hard Coal	Hydrogen
Crude Oil	0.23	0.49	0.23	0.49
Natural Gas	0.49	1.67	0.49	1.67
Hard Coal	0.23	0.49	0.25	0.49
Hydrogen	0.49	1.67	0.49	1.67

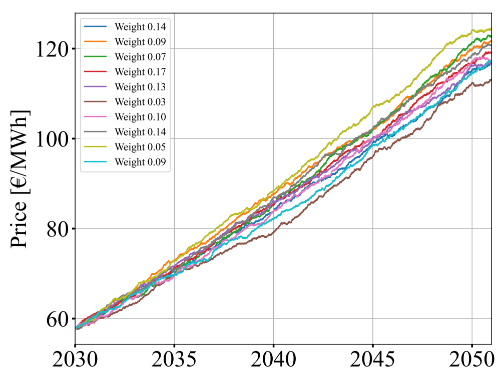
Appendix A.4. Representative fuel price paths



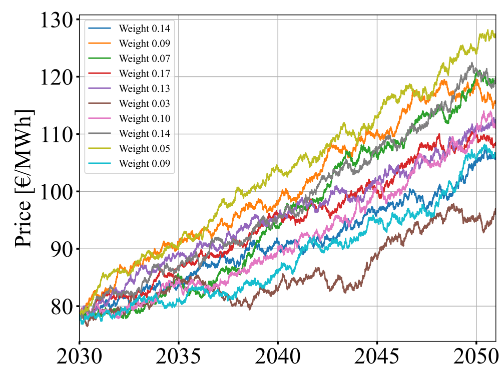
(a) Cluster representatives for crude oil, weighted by path probability.



(b) Cluster representatives for natural gas, weighted by path probability.



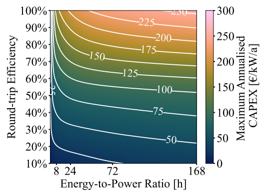
(c) Cluster representatives for hard coal, weighted by path probability.



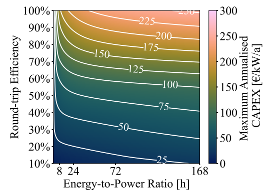
(d) Cluster representatives for Hydrogen, weighted by path probability.

Figure A.10: Cluster representative fuel price paths for each fuel type over the full time horizon, with legend indicating the weight of each path.

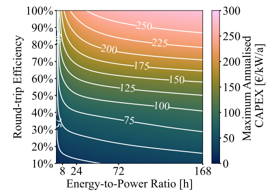
Appendix A.5. Contribution Margins for Storage Parameter Combinations for $\lambda = 0$



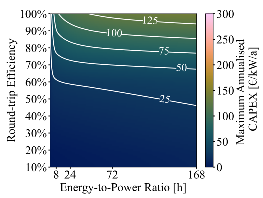
(a) Germany 2035



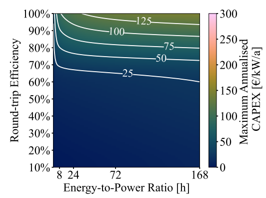
(b) Germany 2040



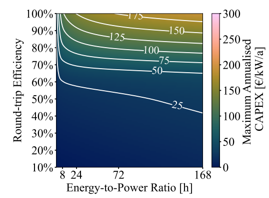
(c) Germany 2045



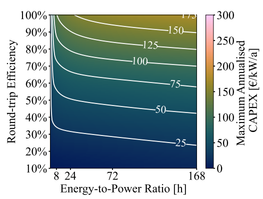
(d) France 2035



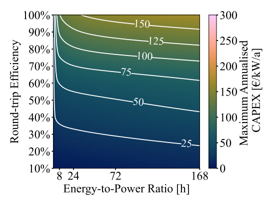
(e) France 2040



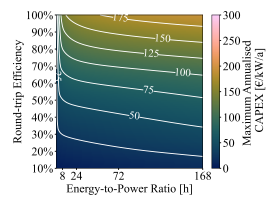
(f) France 2045



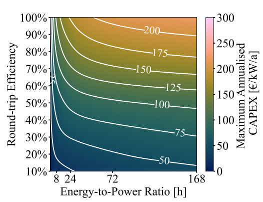
(g) Switzerland 2035



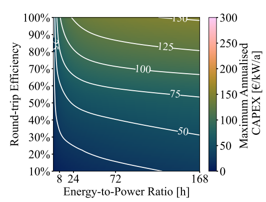
(h) Switzerland 2040



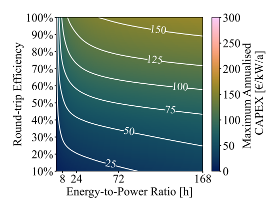
(i) Switzerland 2045



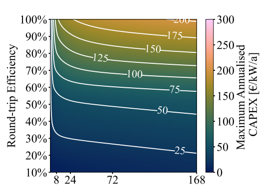
(j) Denmark 2035



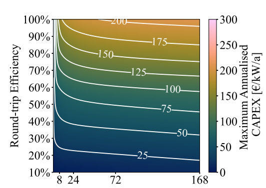
(k) Denmark 2040



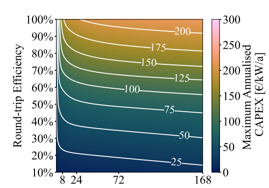
(l) Denmark 2045



(m) Spain 2035



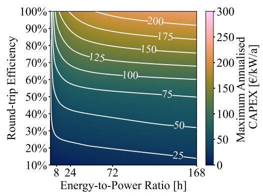
(n) Spain 2040



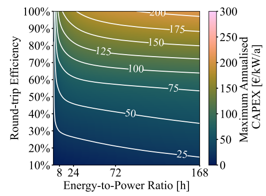
(o) Spain 2045

Figure A.11: Maximum annualised CAPEX for all analysed countries (rows) and years (columns) with $\lambda = 0$.

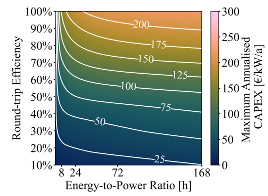
Appendix A.6. Contribution margins for storage parameter combinations for $\lambda = 1$



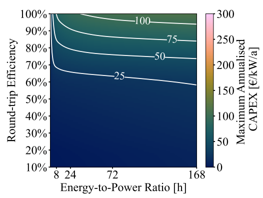
(a) Germany 2035



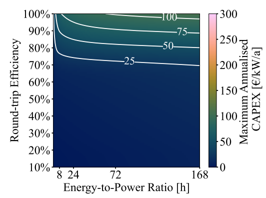
(b) Germany 2040



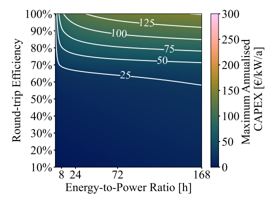
(c) Germany 2045



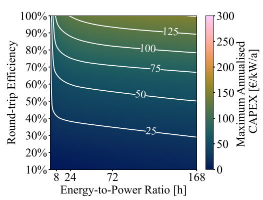
(d) France 2035



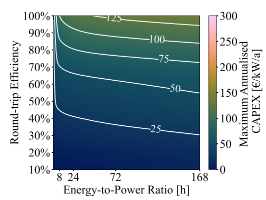
(e) France 2040



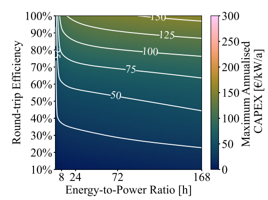
(f) France 2045



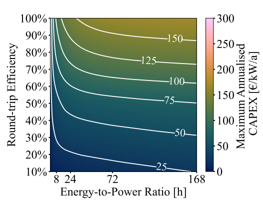
(g) Switzerland 2035



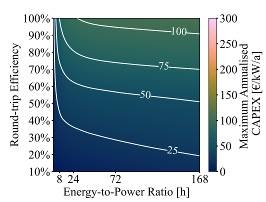
(h) Switzerland 2040



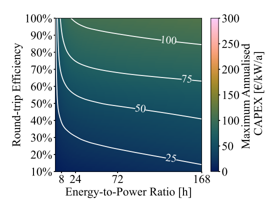
(i) Switzerland 2045



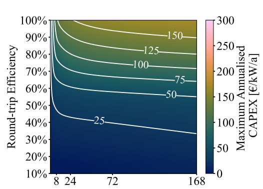
(j) Denmark 2035



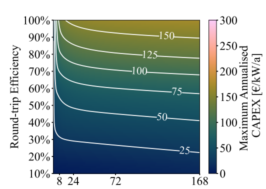
(k) Denmark 2040



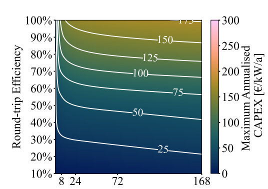
(l) Denmark 2045



(m) Spain 2035



(n) Spain 2040



(o) Spain 2045

Figure A.12: Maximum annualised CAPEX for all analysed countries (rows) and years (columns) with $\lambda = 1$.

Appendix B. Additional methods

Appendix B.1. Average daily spreads

The average daily spreads, shown in Figure 4, are calculated as follows: For each day d, let $P_{d,1}, P_{d,2}, \ldots, P_{d,24}$ denote the set of hourly prices. We define the n-th largest and n-th smallest prices as $P^{\downarrow}_{d,(n)}$ and $P^{\uparrow}_{d,(n)}$, respectively. The daily n-spread is computed as

$$S_d^{(n)} = P^{\downarrow}_{d,(n)} - P^{\uparrow}_{d,(n)} .$$

The mean daily n-spread over all days D is

$$\overline{S}^{(n)} = \frac{1}{|D|} \sum_{d \in D} S_d^{(n)} .$$

$S_d^{(n)}$ represents the difference between the n-th largest and n-th smallest hourly price within a single day, and $\overline{S}^{(n)}$ summarizes this measure across the entire dataset.

Appendix B.2. Mathematical representation of weather scenario weights

We consider I weather scenarios $i \in \mathcal{I} = \{1, ..., I\}$, each with hourly values for renewable generation capacity factors and electricity demand as component $c \in \mathcal{C}$. The scenario probability w_i^w is computed through a weighted aggregation over areas $a = 1, \ldots, A$, components $c = 1, \ldots, C$, and months $m = 1, \ldots, 12$. For each component c in area a and month m, the monthly mean over hours h is calculated as:

$$\bar{x}_{i,a,c,m} = \frac{1}{n_m^h} \sum_{h \in \text{ month } m} x_{i,a,c,h} \tag{B.1}$$

where $x_{i,a,c,h}$ denotes the hourly value of scenario i, component c, and area a, and n_m^h is the number of hours in month m. The monthly mean across all scenarios is

$$\mu_{a,c,m} = \frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \bar{x}_{i,a,c,m} \tag{B.2}$$

The deviation of a scenario from the mean is

$$\Delta_{i,a,c,m} = \bar{x}_{i,a,c,m} - \mu_{a,c,m} \tag{B.3}$$

The standard deviation across scenarios is

$$\sigma_{a,c,m} = \sqrt{\frac{1}{|\mathcal{I}|}\sum_{i\in\mathcal{I}}(\bar{x}_{i,a,c,m} - \mu_{a,c,m})^2} \tag{B.4}$$

The deviation is assigned to bins as follows:

$$\text{Bin}_{i,a,c,m} = \begin{cases} \text{Bin 1}, & \Delta_{i,a,c,m} < -2\sigma_{a,c,m} \\ \text{Bin 2}, & -2\sigma_{a,c,m} \leq \Delta_{i,a,c,m} < -\sigma_{a,c,m} \\ \text{Bin 3}, & -\sigma_{a,c,m} \leq \Delta_{i,a,c,m} < 0 \\ \text{Bin 4}, & 0 \leq \Delta_{i,a,c,m} < \sigma_{a,c,m} \\ \text{Bin 5}, & \sigma_{a,c,m} \leq \Delta_{i,a,c,m} < 2\sigma_{a,c,m} \\ \text{Bin 6}, & \Delta_{i,a,c,m} \geq 2\sigma_{a,c,m} \end{cases} \tag{B.5}$$

The probability per bin is

$$w^{\text{bin}}_{i,a,c,m} = \frac{\text{Number of scenarios in the same bin}}{|\mathcal{I}|} \tag{B.6}$$

The component weight is

$$w^{\text{comp}}_{a,c} = \frac{\text{Capacity or demand of component } c \text{ in area } a}{\sum_{a'=1}^{A} \text{Capacity or demand of component } c \text{ in all areas}} \tag{B.7}$$

The total scenario probability is computed by summing over all areas, components, and months:

$$w^{w}_{i} = \sum_{a=1}^{A}\sum_{c=1}^{C}\sum_{m=1}^{12} w^{\text{comp}}_{a,c} \cdot w^{\text{bin}}_{i,a,c,m} \tag{B.8}$$

with

$$\sum_{i\in\mathcal{I}} w^{w}_{i} = 1$$

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