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WORKING PAPER

Battery and Hydrogen Storage: Complements or Substitutes? A German 2035 Case Study

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Underground Hydrogen Storage (UHS) is regarded as a key solution for seasonal energy storage in variable renewable energy (VRE)-intensive systems. While UHS is often seen as complementary to short-term storage solutions such as Battery Energy Storage Systems (BESS), the true extent of their complementary or substitutive relationship remains an open question. This paper examines the interaction between UHS and BESS in a low-carbon German energy system in 2035 using a multi-stage stochastic dynamic programming model solved by implementing the Stochastic Dual Dynamic Programming (SDDP) algorithm. Optimizing investment and dispatch over a year with hourly resolution, we compute the Morishima elasticity of substitution between the two technologies. Results show that UHS and BESS act as economic substitutes rather than complements. Notably, substitution is asymmetrical: a reduction in BESS costs leads to a proportionally greater shift toward BESS investment relative to UHS (elasticity of 3), whereas the effect of UHS cost changes on investment decisions is weaker (elasticity of 1). Consistent with prior studies, we also find that UHS revenues are highly volatile and heavily dependent on the concurrent development of hydrogen infrastructure. Adding to these two main shortfalls for UHS's business case in future energy systems, our findings thus highlight a third layer of uncertainty for UHS — competition from BESS, which can partially replace it and reduce its economic viability. In contrast, BESS investments are less dependent on external factors, making them a more attractive option.

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KEYWORDS

Hydrogen storage | Battery storage | Substitution | Stochastic programming

Executive summary

This study investigates the relationship between Battery Energy Storage Systems (BESS) and Underground Hydrogen Storage (UHS) in the context of a low-carbon German energy system by 2035. We assess how these two technologies act as substitutes or complements using a multi-stage stochastic dynamic programming model solved with the Stochastic Dual Dynamic Programming (SDDP) algorithm. The analysis reveals that BESS and UHS are economic substitutes rather than complements, with an asymmetric substitution effect: changes in BESS costs have a more significant impact on investment decisions than changes in UHS costs.

Key Findings

- BESS and UHS are imperfect substitutes. More precisely, they exhibit an asymmetric elasticity of substitution, and their optimal investment decision is three times more sensitive to BESS's cost than to UHS's (elasticity of 3 and 1, respectively). This shows UHS may not be shielded from competition from short-duration storage.
- UHS investment is highly dependent on developing hydrogen infrastructure, highlighting a "chicken-and-egg" problem where both UHS and hydrogen turbines are necessary for each other's viability.
- UHS profits are very volatile. The investment in UHS is driven by a handful of years of very uneasy weather conditions (low PV and wind output with a bad correlation to demand). This creates a highly skewed profit distribution, with some years of very high profits and the majority with negative profits for UHS operators.

Policy Recommendations

- Our results show UHS will likely not develop on its own. This is partly due to market failures hindering the ability of project developers to trade risk. The State can help by stepping in and proposing derisking schemes like Contracts-for-Difference (CfDs).
- Even with such tools, we find evidence that UHS may not be able to thrive due to competition from other storage technologies like BESS, which shows declining costs. Hydrogen-focused support schemes may thus distort the equilibrium. Technology-agnostic measures are better suited to ensure all storage options are on the same level playing field.

Conclusions

The study concludes that while BESS and UHS serve distinct roles in the energy system, they are substitutes rather than complements. The asymmetric substitution effect and the challenges faced by UHS, such as profit volatility and infrastructure dependency, highlight the difficult business case of this technology. Future research should explore the interactions between these storage technologies and other flexibility options to inform energy policy and investment decisions further.

1. Introduction

In most decarbonization scenarios, the joint deployment of Variable Renewable Energy (VRE) sources and carbon-free electrofuels is central to reaching climate neutrality (DeAngelo et al., 2021). Yet, given the non-dispatchable and variable nature of VREs, such as solar and wind technologies, their deployment needs to be complemented by investment in flexibility assets to ensure the adequacy of supply and demand at all times (Kondziella and Bruckner, 2016).

"Flexibility" can be defined as the ability to adjust supply and demand to achieve the energy balance (Cochran et al., 2022). Electricity systems require flexibility over various timescales, from seconds to seasons (Alidazeh et al., 2016). Historically, thermal power plants have performed load-following operations to manage sudden and often unpredictable changes in electricity demand. However, the rapid expansion of VREs has introduced new short-term flexibility needs, as their output can fluctuate quickly, amplifying demand variability. Over seasonal timescales, additional flexibility solutions are also required to address prolonged periods of energy scarcity — known as dark doldrums or Dunkelflaute — by leveraging surplus renewable generation from other times of the year. To address these new flexibility needs, some options are exclusively part of the power system, such as flexible generation, electricity storage, grid expansion, demand response, or VRE curtailment. In contrast, others link the power sector to other sectors, such as electric vehicles, heat pumps, or power-to-gas (PtG) (Roach and Meeus, 2020).

Among all these flexibility options, energy storage plays a crucial role by enabling surplus electricity produced during periods of high production to be stored and released during periods of low production or high demand. Various technological options for storage exist, each suited to different uses based on their technical characteristics and cost structures (Lund et al., 2015). Among these, Battery Energy Storage System (BESS) and hydrogen storage, particularly Underground Hydrogen Storage (UHS), are generally presented as promising candidates for short-term and long-term needs, respectively (Dowling et al., 2020). Indeed, BESS and UHS have contrasting cost structures: BESS displays high energy (MWh) costs relative to power (MW), while UHS has low energy costs but high power capacity costs. As a result, their optimal energy-to-power ratios vary widely, from a few hours for BESS to several hundred for UHS (Lund et al., 2015). Due to these characteristics, UHS is regarded as a strong candidate for seasonal storage (Petkov and Gabrielli, 2020), while BESS is better suited for delivering high power output over shorter durations.

The role of storage in providing flexibility services has been extensively studied, with Blanco and Faaij (2018) and Schill (2020) conducting dedicated literature reviews on the topic. They both show that storage needs depend on the share of energy supplied by renewable electricity and the cost and availability of the other flexibility options in the system. Storage becomes more relevant for high VRE penetration levels and is essential for achieving fractions over 80%. Several articles examine the combined need for different storage technologies in future energy systems. For instance, Thimet and Mavromatidis (2023) study storage development in six decarbonization scenarios for the German electricity system. They show that existing Pumped-Hydro Storage (PHS) will meet storage needs until 2030, but additional BESS and UHS will be required for daily and seasonal needs thereafter. Victoria et al. (2019) examine the role of storage for achieving 95% CO_2 reductions in the European energy system. They demonstrate that BESS storage is cost-optimal for mitigating hourly fluctuations in solar output. In contrast, hydrogen storage is preferred for smoothing multi-day wind fluctuations. They found that the coexistence of these two storage technologies is expected in the future European energy system to offer flexibility services at different timescales. However, other articles have already shown that BESS and UHS technologies can compete with each other as they provide a similar service to the system, even though they have hardly quantified this substitution effect. For instance, Gawlick and Hamacher (2023) investigate the development of storage and transmission infrastructures in a zero-emission European electricity-hydrogen system in 2050. Their findings indicate that when the electricity and hydrogen sectors are coupled, part of the battery storage is replaced by hydrogen storage. Marocco et al. (2023) examine the role of BESS and UHS in achieving a 100% renewable energy system. By comparing scenarios with and without hydrogen storage, they demonstrate that some services provided by BESS can be substituted by UHS, indicating partial substitution between these two technologies. Loschan et al. (2024) study the competition and synergies between different flexibility providers in Austrian and German case studies. They show that increasing storage capacity lowers high electricity prices and raises low electricity prices. As a result, UHS and BESS compete in the electricity market because increased storage capacity narrows the electricity price spread, on which storage operators depend for remuneration. To our knowledge, no work in the literature explicitly quantifies the substitution between BESS and UHS in future combined electricity-hydrogen energy systems.

This paper aims to fill this gap by evaluating the degree of substitutability between these two energy storage assets. From a methodological perspective, our study differs from the previously cited articles by adopting a stochastic approach. In future energy systems with a high proportion of VRE, episodes of high VRE production — or, conversely, periods of extensive renewable energy scarcity — are likely to occur periodically. However, the timing, duration, and frequency of these events are unpredictable and can vary significantly from year to year, depending on weather conditions. Consequently, determining the appropriate level of investment in long-term energy storage and deciding how to operate it becomes a stochastic problem (Boffino et al., 2019; Liu et al., 2018), as it serves as insurance against prolonged energy shortages, the latter being inherently unpredictable (Petkov and Gabrielli, 2020). Sioshansi et al. (2011), for instance, show that compressed air energy storage can experience critical variations in arbitrage value, with some years being twice as profitable as others. To account for this randomness, stochastic programming is the state-of-the-art approach, as deterministic algorithms have been shown to perform poorly in comparison — even with highly accurate forecasts and in systems without renewable generation (Philbrick and Kitanidis, 1999). We develop a Multi-stage Stochastic Dynamic Programming (MSDP) model that optimizes production and storage decisions in an electricity-hydrogen system. The model is calibrated for a one-year horizon with an hourly time step to reflect the dynamic operations of both daily and seasonal storage assets. An MSDP with high time resolution that covers electricity and hydrogen markets poses computational challenges, addressed using the Stochastic Dual Dynamic Programming (SDDP) algorithm (Pereira and Pinto, 1991). The investment decisions derived from the model are used to assess the elasticities of substitution between UHS and BESS, measuring how changes in the cost of one storage technology affect the optimal investment in the other. Since other technologies also adapt to the change in cost, we use the Morishima elasticity of substitution, which accounts for such multi-input effects. We use Germany as a case study, which has significant geological potential for developing UHS (more than 40% of the European capacity in salt caverns (Caglayan et al., 2020)), and which relies on this technology and on BESS to support its energy transition (German Federal Government, 2023).

Our findings indicate that BESS and UHS function as substitutes in economic terms, meaning they are better characterized as competitors rather than complementary technologies. Additionally, we find that this substitution is asymmetric: the optimal capacity ratio of UHS to BESS is significantly more sensitive to changes in BESS costs than to UHS costs, with substitution elasticities of 3 and 1, respectively. On the other hand, UHS stands out as a critical technology for the system to cope with dark doldrums events, a role BESS can only imperfectly handle. UHS thus resembles a necessity good for integrated electricity-hydrogen systems, whereas BESS acts more like a luxury good since its main use resides in displacing gas turbines. When computing the revenue distribution of BESS and UHS operators for 200 climatic years, we find UHS' profits to be much more volatile than BESS'. We also perform a sensitivity analysis on the exogenously installed capacity of hydrogen turbines, and we find the UHS investment capacity to vary widely according to that assumption. Investment in UHS thus faces three main challenges: (i) highly volatile profits, which may deter risk-averse investors; (ii) strong dependence on the development of broader hydrogen infrastructure, highlighting the well-known chicken-and-egg problem; and (iii) competition from alternative storage technologies like BESS, which can reduce the need for UHS. While the first two challenges have been previously recognized, this study is, to our knowledge, the first to systematically examine the impact of storage competition on UHS deployment.

This paper is organized as follows. Section 2 presents the methods, the case study, as well as the scenarios used to investigate the interplay between BESS and UHS. The main results are presented in Section 3.

2. Methodology

First, we describe our electricity-hydrogen framework and the energy system model used to optimize the operations and investment decisions (Section 2.1). Second, we apply the microeconomic concept of elasticity of substitution to assess the extent to which UHS and BESS can substitute for each other (Section 2.2). Finally, our case study on the German energy system for 2035, as well as our variant and scenarios, are detailed (Sections 2.3 and 2.4 respectively).

2.1. Multi-Stage Dynamic Programming Model

To evaluate the interaction between UHS and BESS, we employ an MSDP model, which simulates investment and dispatch decisions made by a benevolent planer — equivalently, a myriad of risk-neutral economic actors in a perfect competition landscape — in an integrated electricity-hydrogen market under uncertainty. Accounting for variable renewable energy sources (VREs) inherent generation variability is critical in this context, as UHS is designed to handle long-term storage needs. For this reason, stochasticity in VRE production and power demand is explicitly incorporated using the MSDP framework. The model's primary objective is to minimize the expected total cost of the electricity and hydrogen system. Costs include investment costs, fixed and variable operation and maintenance costs (O&M), and value of loss load (VoLL). We consider a one-year time horizon to account for seasonal variations in energy supply and demand and consider timeframes of one hour long to capture the behavior of short-term storage, as preconized in the literature (Petkov and Gabrielli, 2020; Merrick et al., 2024).

Figure 1 describes the proposed electricity-hydrogen system. It includes VREs alongside flexible generation technologies such as gas turbines (GT), hydrogen turbines (HT), and biomass. The import and export of electricity from neighboring regions are allowed. Energy storage options — pumped hydro storage (PHS), UHS, and BESS — are also included. Additionally, hydrogen can be produced from electricity using PtG, gas using steam methane reforming (SMR), or imported. The only allowed investment decisions are for UHS and BESS, while the capacities of other technologies (e.g., gas turbines, biomass, imports, hydropower) are fixed. Their hourly dispatch is, however, endogenously determined by the model. Investment decisions occur at the beginning of the modeled year and condition the use of the two assets within the year.

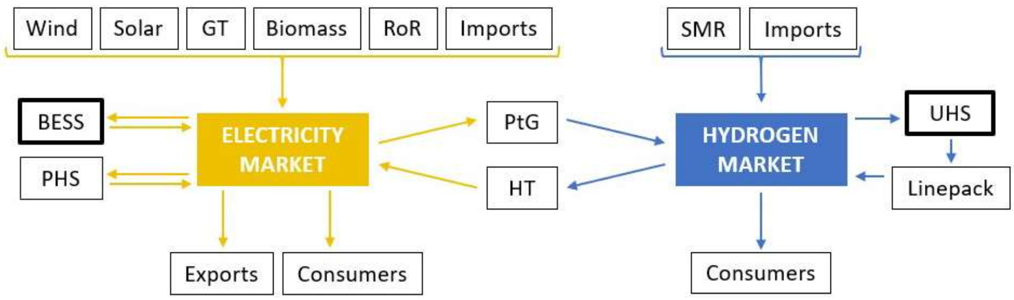


Figure 1: Overview of the electricity and hydrogen system model.

In dynamic programming, the full cost minimization problem is broken down into subproblems corresponding to distinct time periods called stages. Each stage represents a period in time within the planning horizon where no uncertainty prevails. Within this framework, variables are classified into state, decision, and random variables. State variables capture the system's condition at a given stage—such as the storage level — determined by past states. Decision variables represent choices made at each stage, such as the hourly dispatch of thermal power plants to balance supply and demand. Random variables account for uncertainties, including solar and wind generation and electricity demand. In our model, each stage represents one week, resulting in 52 stages over the year. This structure strikes a balance between temporal granularity and computational feasibility by leveraging the reliability of weather forecasts up to one week ahead (Cheng et al., 2021). A weekly stage length preserves temporal correlations within the same week, which would be lost with a daily stage approach. Additionally, it offers a practical tradeoff between representing a wide range of climatic years and maintaining model tractability. At the start of each stage, random variables representing VRE production and demand for the upcoming 168 hours are revealed. Figure 2 summarizes the structure of the decision-making process under uncertainty.

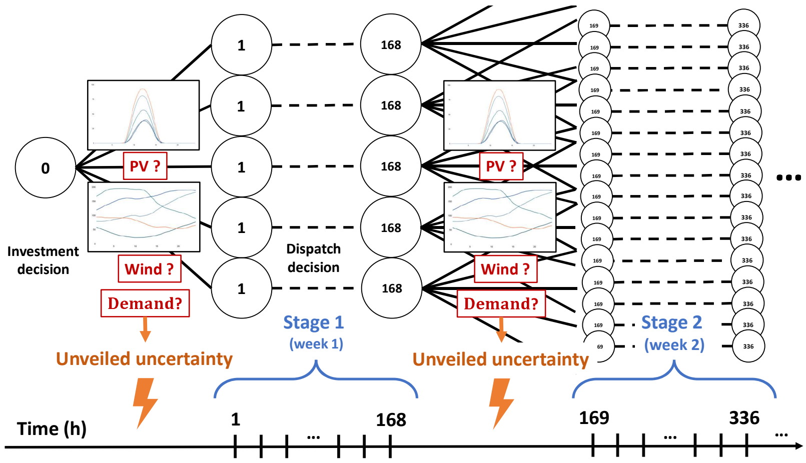


Figure 2: Stylized view of the decision tree used in the model

The optimization process aims to select a set of decisions that minimize the total expected cost over the time horizon while satisfying the technical constraints inherent in energy systems. This intertemporal cost minimization problem is presented in eq (1):

$$\min_{(l_1,u_1)\in F_1} C_1(l_1,u_1) + \mathbb{E}_{\xi_2\in\Omega_2}\left[\min_{(l_2,u_2)\in F_2(l_1,\xi_2)} C_2(l_2,u_2,\xi_2) + \mathbb{E}_{\xi_3\in\Omega_3}\left[\dots \right.\right. \tag{1}$$

$$\left.\left. + \mathbb{E}_{\xi_{52}\in\Omega_{52}}\left[\min_{(l_{52},u_{52})\in F_{52}(l_{51},\xi_{52})} C_{52}(l_{52},u_{52},\xi_{52})\right]\right]\right].$$

The cost function $C_w(l_w, u_w, \xi_w)$ represents the cost of system at stage w, where l_w represents the state variable vector and u_w the decision variable vector. The random variable, drawn from the sample space Ω_w, is denoted by ξ_w. The feasible region at stage w, denoted by $F_w(l_{w-1}, \xi_w)$, is determined by the prior state l_{w-1} and the realized value of ξ_w.

Traditional stochastic dynamic programming requires discretizing state variables and exploring all possible futures, leading to computational intractability for large systems—a challenge known as the "curse of dimensionality." To address this, we employ the Stochastic Dual Dynamic Programming (SDDP) algorithm developed by Pereira and Pinto (1991). SDDP approximates the expected value of future costs using dual solutions instead of state discretization, making it suitable for large-scale multistage problems that require high temporal resolution and extended horizons (Merrick et al., 2024). Following the methodology detailed in Blanchard (2024), we implement our model using the Julia SDDP.jl package (Dowson and Kapelevich, 2021) with the CPLEX solver.

The model enforces hourly supply-demand balance for both electricity and hydrogen (equations in Appendix A). All technologies operate within their capacity limits, including dispatchable generation, storage, and cross-border flows. Storage facilities are constrained by charging/discharging rates and total capacity, with UHS limited to twelve annual cycles via linear approximation.[1]. In the electricity sector, supply must cover demand, which includes consumption, power-to-hydrogen conversion, UHS compression, storage charging, and exports. We assume a constant hourly demand for hydrogen, reflecting its anticipated future role, primarily driven by industrial processes with minimal short-term variability (German Federal Government, 2020). Hydrogen supply in the model comes from SMR, PtG, UHS discharge, and imports.

2.2. Definition of the Morishima elasticity of substitution

The concept of elasticity of substitution has played a central role in microeconomic theory, particularly in understanding how firms adjust input combinations in response to changes in relative prices. The earliest and most widely known definition, introduced by Hicks (1932), describes the ease with which two inputs can be substituted while maintaining constant output. This elasticity is formally expressed as:

$$\sigma = \left(\frac{\partial \ln \left(MRTS_{x_1,x_2} \right)}{\partial \ln \left(x_2/x_1 \right)} \right)^{-1}, \tag{2}$$

where x_1 and x_2 are two inputs, and $MRTS_{x_1,x_2}$ represents the marginal rate of technical substitution. This formulation applies strictly to a two-input production function where output is held constant. However, real-world production processes rarely involve just two inputs, necessitating extensions of this concept. Recognizing the need to handle multiple inputs, Hicks and Allen (1934) introduced an elasticity measure later formalized by Uzawa (1962) as the Allen-Uzawa elasticity of substitution (AUES). This measure is derived from the second derivatives of the cost function and has been widely used in empirical studies (Blackorby and Russell, 1989).

However, it has been criticized for failing to preserve key properties of Hicks' original measure, particularly in its inability to provide an intuitive measure of substitution ease or capture changes in relative factor shares. To address these

[1]For an in-depth discussion on how binary cycling constraints can be effectively aggregated into linear constraints at the system level, see (Blanchard and Massol, 2025)

shortcomings, Morishima (1967) proposed the Morishima elasticity of substitution (MES), later advocated by Blackorby and Russell (1989) as the appropriate generalization of Hicks' notion when dealing with more than two inputs. Unlike AUES, MES directly measures how the ratio of two inputs changes in response to a change in their relative prices while allowing for adjustments in the use of other inputs. Unlike Hicks or Allen-Uzawa elasticities, MES is inherently asymmetric, meaning that the ease with which one input replaces another when its price increases may differ from the reverse case. The sign of MES determines the nature of the relationship between two inputs: if MES is positive, the inputs are substitutes, as an increase in the cost of one leads to an increase in the use of the other. Conversely, a negative MES indicates that the inputs are complements, meaning that an increase in the cost of one results in a decline in the use of the other. In the extreme case of perfect substitutes, MES tends toward infinity, indicating that one input can fully replace the other without efficiency loss.

In our model, investments in UHS and BESS respond to changes in their respective marginal costs while the rest of the power system — including gas turbines, solar, wind, and other technologies — adjusts to maintain supply-demand adequacy. These adjustments are driven by stochastic variations in weather conditions, meaning that production patterns from renewables and dispatchable sources fluctuate across different simulation runs. Fixing their output levels, as required in Hicksian and Allen-Uzawa formulations, would strip the model of its stochastic nature and misrepresent real-world flexibility needs. Given this, we use the Morishima elasticity of substitution, which is formally defined as:

$$\sigma^M_{x_1,x_2} = \frac{\partial \ln (x_2/x_1)}{\partial \ln (MC_1/MC_2)}, \tag{3}$$

where x_1 and x_2 represent the equilibrium investment levels of UHS and BESS, respectively, and MC_1 and MC_2 are their corresponding marginal investment costs. This measure captures the relative responsiveness of UHS versus BESS investment when their cost ratios change while accounting for the ability of the broader energy system to adapt. To estimate the Morishima elasticity, we perturb the relative marginal investment cost of BESS and UHS (MC_1/MC_2) and observe the resulting changes in their equilibrium capacities (x_2/x_1). The elasticity is computed as the slope of the relationship between $\ln(x_2/x_1)$ and $\ln(MC_1/MC_2)$.

Our analysis relies on a cost-minimization framework to determine optimal investment in BESS and UHS, as well as the optimal dispatch of all technologies throughout the year. While real-world market operators do not minimize costs but rather maximize profits, it is known that under perfect competition, the outcomes of a benevolent social planner minimizing system costs and a decentralized market with profit-maximizing firms coincide — provided that demand is perfectly inelastic (Kirschen and Strbac, 2019). This assumption is reasonable in the short run, as electricity consumption is largely unresponsive to price fluctuations. Therefore, despite using an optimization model rather than a formal market equilibrium model, the investment and dispatch decisions derived from our framework remain consistent with those of a perfectly competitive market. As a result, equation (3) can be interpreted as the MES between UHS and BESS.

2.3. Application case: German energy system in 2035

We calibrate our model to represent a future electricity and hydrogen system that includes both BESS and UHS, using the future German energy system as a reference. Germany aims for 100 percent decarbonized, VRE-based electricity generation by 2035, necessitating increased flexibility and storage resources. Germany has significant geological potential for developing UHS (more than 40% of the European capacity in salt caverns (Caglayan et al., 2020)) and relies on this technology, along with BESS, to meet future storage needs. Indeed, even though PHS capacities are sufficient to meet flexibility needs until 2030, the development of battery and UHS storage capacities is essential for accommodating a larger share of VRE production (Thimet and Mavromatidis, 2023; German Federal Government, 2023).

A 100% decarbonized German electricity system by 2035 has been examined by the German think tank Agora Energiewende in 2022[2] (Energiewende, 2022). Their study suggests that achieving this target requires substantial growth in VRE capacities and the repurposing of a significant portion of gas turbines as hydrogen turbines (approximately one-third). Combined with the ambitious decarbonized hydrogen development goals outlined in the German hydrogen strategy (German Federal Government, 2020), this scenario provides a framework that necessitates both BESS and UHS capacities. We use this scenario as a reference to study the interplay between these two storage sources. The associated data are presented in Appendix B. Although this scenario aligns with Germany's targets, it is very ambitious. Therefore, Section 3.4 includes a sensitivity study that considers a lower quantity of gas turbines being repurposed into hydrogen turbines, examining the interplay between BESS and UHS in a context where not all decarbonization goals are fully achieved.

[2]The 100% decarbonized grid is defined as the annual share of VRE generation relative to total demand, allowing fossil gas plants for hourly supply adequacy while attributing 100% decarbonized production due to exports. This definition follows the German government's targets as outlined in the Agora Energiewende report.

2.4. Data

We analyze the substitutability between UHS and BESS through two separate sensitivity analyses, using baseline investment costs from literature: EUR 245/kWh for BESS and EUR 2.58/kWh (including compressors, drying and Pressure Swing Adsorption, PSA) for UHS (RTE, 2021; Michalski et al., 2017). We investigate the relative substitution patterns between BESS and UHS by simulating investment cost variations for each technology while keeping the other constant. Specifically, we first analyze how the ratio of installed capacities between UHS and BESS evolves when UHS costs vary while BESS costs remain fixed. Conversely, we examine how this ratio responds when BESS costs change while UHS costs remain constant. By regressing the logarithm of the installed capacity ratio on the logarithm of the cost ratio, we estimate the Morishima elasticity of substitution, which captures the asymmetric responsiveness of investment decisions to relative cost changes. To estimate the elasticity of substitution through regression analysis, we simulate five different investment cost scenarios for each technology, ranging from 20% to 200% of baseline costs (20-150% for UHS and 50-200% for BESS for practical computational reasons) as shown in Table 1. Investment costs for both storage technologies are annualized using the following formula and a 5% discount factor:

$$C^{\text{ann}} = C^{\text{inv}} \times \frac{r}{1-(1+r)^{-T}} \tag{4}$$

where C^{ann} is the annualized investment cost, C^{inv} is the upfront investment cost, $r = 0.05$ is the discount rate, and T denotes the economic lifetime of the asset. The total annuity considered in the model also encompasses fixed O&M costs, which are added to the annualized investment expenditure.

Case	**Technology**	**Annuity** *(EUR/MWh)*				
Case 1	BESS	31,100 (constant)				
	UHS	167	250	333	500	666
Case 2	BESS	6,220	15,550	23,325	31,100	46,650
	UHS	333 (constant)				

Table 1: Investment Cost Scenarios for UHS and BESS Analysis Cases

3. Results

3.1. Substitutability Between UHS and BESS

3.1.1. Relative Investment Response to UHS Cost Variations

To assess how the relative deployment of BESS and UHS responds to changes in UHS costs, we conduct a regression analysis following equation (3). Specifically, we regress the logarithm of the ratio of investments in BESS to UHS on the logarithm of the relative cost of UHS to BESS. The estimated equation is:

$$\ln\left(\frac{\text{BESS}}{\text{UHS}}\right) = 1.1 \ln\left(\frac{\text{cost}_{\text{UHS}}}{\text{cost}_{\text{BESS}}}\right) - 0.26, \tag{5}$$

The estimated slope coefficient of 1.1 represents the elasticity of substitution when the cost of UHS changes while BESS costs remain fixed. This suggests that a 1% increase in the relative cost of UHS leads to an approximately 1.1% increase in the investment ratio of BESS to UHS. However, it is essential to clarify that this does not imply a one-to-one replacement of UHS by BESS. Instead, it reflects how investment in BESS adjusts relative to UHS under cost variations, while other energy system components simultaneously adapt. The relatively strong coefficient of determination ($R^2 = 0.94$) suggests that most of the variation in investment ratios is explained by the model.

3.1.2. Relative Investment Response to BESS Cost Variations

To evaluate the inverse case, we regress the logarithm of the UHS-to-BESS investment ratio against the logarithm of the relative cost of BESS to UHS when BESS costs are changed. The resulting equation is:

$$\ln\left(\frac{\text{UHS}}{\text{BESS}}\right) = 2.9 \ln\left(\frac{\text{cost}_{\text{BESS}}}{\text{cost}_{\text{UHS}}}\right) - 7.7, \tag{6}$$

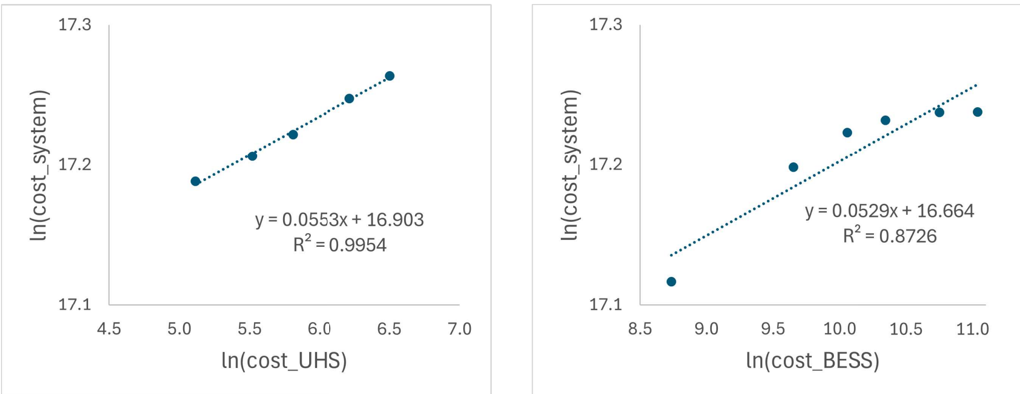
with a coefficient of determination $R^2 = 0.97$. Here, the estimated elasticity of 2.9 indicates that a 1% increase in the cost of BESS leads to an approximate 2.9% increase in the ratio of UHS to BESS investment. This suggests that UHS investment is significantly more sensitive to BESS cost variations than vice versa.

3.1.3. Understanding the asymmetry

The results reveal a clear asymmetry in the estimated elasticities of substitution between UHS and BESS. Specifically, when the cost of BESS increases, the system shifts toward UHS at a higher rate ($\sigma = 2.9$), whereas when the cost of UHS increases, the response toward BESS is comparatively weaker ($\sigma = 1.1$). In economic textbooks, substitution is often presented as symmetric: if one input replaces another, the reverse should hold to the same extent. However, asymmetric substitution arises when one input can replace another more effectively than the reverse due to differences in functionality, constraints, or systemic interactions. A useful analogy comes from the labor market, as discussed in De Jaegher (2009): consider skilled and unskilled workers. Skilled workers can perform tasks typically handled by unskilled workers — albeit less efficiently — but the reverse is much less feasible. For instance, during economic downturns, unskilled workers are more vulnerable to layoffs because skilled workers can take over their roles if needed. However, if wages for skilled workers rise, firms have limited ability to replace them with unskilled labor due to skill constraints.

This mirrors the asymmetric substitution dynamics observed between UHS and BESS. When BESS costs rise, UHS partly compensates, but the system also turns to gas turbines, which typically compete with batteries. In contrast, when UHS costs increase, alternatives are more limited. UHS operates during prolonged energy shortages when other resources are already at full capacity. In response, the model invests more in BESS, using part of its capacity for longer-duration storage despite its lower efficiency for this role.

Another way to interpret this asymmetry is through the economic distinction between necessities and luxury goods in consumer theory. UHS behaves more like a necessity, playing a fundamental role in ensuring long-term system flexibility, particularly for hydrogen turbine operations during extended low-renewable periods (e.g., "dunkelflaute" conditions). Its cost structure scales linearly with total system costs, as illustrated in Figure 3a, indicating that even at higher costs, UHS remains essential. By contrast, BESS behaves more like a luxury input: it provides valuable short-term flexibility at low costs but is more easily substituted when its price increases. As shown in Figure 3b, the system exhibits a nonlinear dependence on BESS, with diminishing reliance as costs rise and alternative resources, including UHS, replace it.



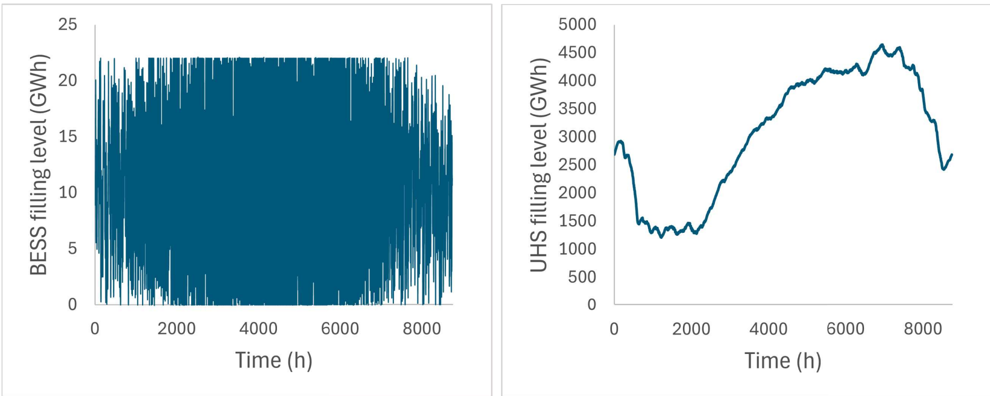
(a) System cost elasticity to UHS investment cost

(b) System cost elasticity to BESS investment cost

Figure 3: System cost sensitivity to storage investment costs

3.2. Disantangling UHS and BESS interaction

Stating that BESS and UHS are substitutes in the 2035 German integrated energy system does not imply that only one technology dominates at equilibrium. Rather, because their substitutability is imperfect — as indicated by a Morishima elasticity of substitution close to unity rather than infinity — both technologies coexist, fulfilling distinct roles. This fact is highlighted in Figure 4, which illustrates the filling levels of UHS and BESS throughout the year. BESS follows a daily cycling pattern, shifting excess solar generation from midday to evening demand peaks. This function reduces reliance on gas turbines by smoothing short-term imbalances. However, BESS's limited energy-to-power ratio (4 hours in this model) makes it less efficient for addressing extended periods of energy scarcity. In contrast, UHS operates as a seasonal storage solution, accumulating surplus energy in the spring and summer and discharging it several months later when net electricity demand rises in the fall and winter.



(a) BESS filling level (b) UHS filling level

Figure 4: Comparison of UHS and BESS average filling level along the year

Although their dispatch displays significant differences, Figure 4 also shows the partial substitutability between both technologies. Indeed, a seasonal pattern is observable for batteries, and they typically perform more frequent cycling in the summer than in the winter. This means BESS can help overcome dunkelflaute as well by draining energy from days or weeks before to avoid demand curtailment events. Conversely, UHS is not exclusively a seasonal storage solution; it also responds to short-term fluctuations, as indicated by the subtle variations in its filling level throughout the year. Figure 5 further illustrates these dynamics by showing the electricity system's operation during a winter week with low VRE output and a summer week with high solar generation. In winter, hydrogen turbines play a crucial role in addressing prolonged energy shortages, but BESS also plays a role by balancing energy production from moments of low Loss of Load

Probability (LoLP) to subsequent periods of high energy scarcity. Conversely, in summer, even though UHS does not show a daily cycling pattern, the storage is filled only in hours with the highest VRE production (i.e., around noon when solar panels produce a lot). When the electricity price rises in the evening, electrolysis is stopped, which brings flexibility to the system even at short durations due to the presence of the UHS buffer.

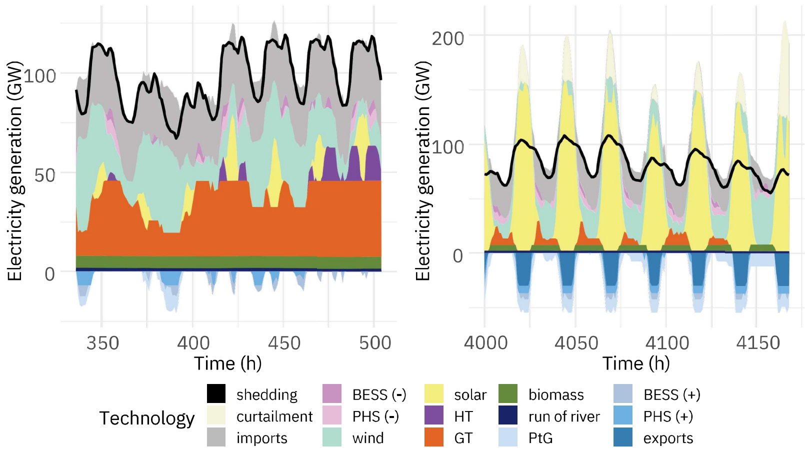


Figure 5: Hourly electricity dispatch for a winter week with low VRE output (left) and a summer week with high solar production (right)

3.3. Profitability and investment risks of UHS and BESS

Figure 6 illustrates the distribution of profits for BESS and UHS net of investment and fixed costs at a 5% discount rate. Since BESS and UHS capacities are endogenously determined, their net average profit is zero.[3] This is because optimization models like ours assume perfect competition, characterized by no entry barrier and risk-neutral investors. Consequently, investments in any particular technology reach but do not exceed the point where revenues equal costs (both fixed and variable), resulting in an average net profit of zero.

A detailed examination of storage profitability over 200 stochastic simulations reveals significant volatility in UHS profits, reflecting its insurance value against extreme energy shortages. This is because UHS derives value primarily from rare but critical periods of high scarcity rents, whose timing and frequency vary unpredictably across climatic years. Some years experience prolonged price

[3]Net of statistical effects, as the mean only approximates the theoretical expectation with a finite number of simulations

spikes, generating substantial profits for UHS, whereas in other years, its utilization remains low, leading to negative profits. This is evident in the negative median profit level, indicating that in most climatic years, UHS operates below its break-even point. However, the presence of a small number of high-profit years offsets these losses, pulling the expected long-run profit to zero. These

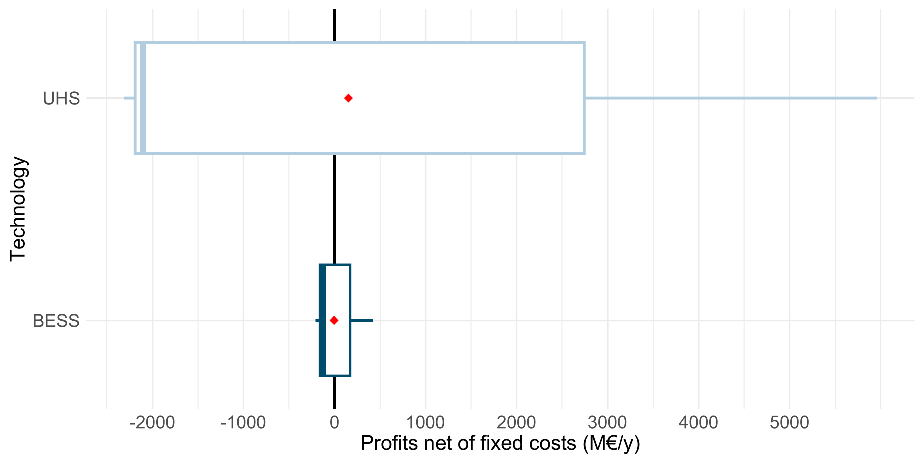


Figure 6: Net profits of storage technologies under the baseline case for fixed costs. The diamond shapes represent average profits over 200 simulated years.

findings raise important concerns regarding investment incentives for UHS. The profit structure observed here closely resembles the missing money problem in liberalized power markets, wherein high-risk but system-critical assets, such as peaking plants, struggle to attract sufficient private investment. The key issue is that energy markets often fail to appropriately value scarcity, leading to suboptimal investment levels in technologies that provide essential reliability services (Bublitz et al., 2019). The case of UHS is particularly relevant in this context: despite its critical role in long-term system balancing, its profitability depends on rare events, making it inherently financially risky for private investors.

3.4. Sensitivity analysis

The case study we have considered is based on a scenario that forecasts the conversion of a significant portion of Germany's gas turbines into hydrogen turbines. However, if this target is not fully met and fewer gas turbines are converted, the coupling between the power and hydrogen systems would be weaker, potentially altering the interactions between UHS and BESS. To examine how the reduced coupling between the electricity and hydrogen sectors impacts investment decisions in UHS and BESS, we ran the model with 5 GW of hydrogen and 57 GW of gas turbines instead of the original 20 GW of hydrogen and 42

GW of gas turbines. With these changes, hydrogen turbines account for 8% of the total turbines, compared to 32% in the original scenario.

This adjusted scenario results in significant changes in storage investments: UHS capacity declines dramatically from 5,300 GWh in the initial scenario to approximately 680 GWh, representing nearly an eightfold reduction. By contrast, BESS investment is less affected, decreasing from 22 GWh to 13 GWh, a reduction of roughly 40%.

This asymmetric response highlights UHS's greater vulnerability to a reduced market coupling between electricity and hydrogen compared to BESS. The substantial reduction in UHS capacity stems from its fundamental dependence on hydrogen turbines for effective integration and operation. The relevance of UHS is tightly linked to the actual deployment of hydrogen turbines. Without substantial investment in these turbines, the business case for UHS collapses, as its role in enabling long-term hydrogen storage and dispatch becomes irrelevant. This interdependence creates a "chicken-and-egg" problem: UHS investments depend on the presence of hydrogen turbines to be meaningful, while hydrogen turbines themselves require UHS to justify their operation. Without UHS, there is little rationale for producing hydrogen-based electricity, as it would not allow for seasonal arbitrage, negating its value as a flexible resource. Consequently, neither technology is likely to develop without the other, making investments in both exceedingly challenging.

In contrast, BESS does not exhibit the same level of dependence on the future development of hydrogen turbines or peaking plants in general. Its relevance and business case are less tied to external developments and more robust to uncertainties in hydrogen infrastructure. This independence makes BESS a more flexible investment, free from the mutual reliance that complicates the viability of UHS and hydrogen turbines.

The reduced coupling between sectors also affects the substitutability between storage technologies. The elasticity of substitution decreases from 2.9 to 2.8 when varying BESS costs and from 1.1 to 0.6 when varying UHS costs. This decline in elasticity values suggests weakened substitutability between UHS and BESS, likely due to the disrupted price correlation between hydrogen and electricity markets. With fewer hydrogen turbines connecting these markets, the operational roles and economic incentives for UHS and BESS investment become less aligned, reducing their ability to substitute for each other.

4. Conclusion

The integration of variable renewable energy (VRE) and carbon-free electrofuels is central to decarbonization strategies, with battery energy storage systems (BESS) and underground hydrogen storage (UHS) often considered complementary solutions for managing system flexibility. This study challenges this assumption by showing that BESS and UHS are better characterized as substitutes rather than complements.

Using a Multi-Stage Stochastic Dynamic Programming (MSDP) model, we optimize investment and dispatch decisions for BESS and UHS in 2035 Germany, accounting for both short-term and long-term flexibility needs. The model incorporates the coupling between electricity and hydrogen markets, including electrolyzer and hydrogen turbine operations, to capture the interactions between these sectors. Since we need to model both short-term and long-term patterns, our model combines an hourly granularity for energy dispatch with a time horizon of one year and a weekly representation of uncertainty on VRE generation. Such a model is hardly tractable, which motivates the use of the Stochastic Dual Dynamic Programming (SDDP) algorithm, an approximation method. We estimate Morishima elasticities of substitution between the two technologies by varying investment costs and analyzing their impact on optimal storage deployment.

Our findings confirm the established operational roles of UHS and BESS: UHS primarily provides seasonal energy storage, while BESS supports short-term storage. However, rather than functioning as complementary assets, we find both technologies to be imperfect and asymmetric substitutes. Optimal investment levels in BESS and UHS are highly responsive to BESS costs (elasticity of 2.9), whereas they show weaker sensitivity to UHS costs (elasticity of 1.1).

These results reinforce known barriers to UHS deployment, including high-profit volatility and dependency on hydrogen infrastructure development, but also introduce a third layer of risk: competition from chemical batteries. As BESS has shown a steady cost decline in the past years, the economic room for seasonal storage through hydrogen becomes thinner.

Three potential extensions could further enhance this study. First, further research is needed to determine whether this substitution effect extends to other battery storage technologies, such as iron-air or flow batteries. Given their lower cost per unit of stored energy compared to the lithium-ion BESS analyzed in this study, these technologies are likely to exert even greater competitive pressure on UHS, further challenging its economic viability. Second, storage is not the only source of flexibility. Future research could explore the interactions between UHS, BESS, and a broader range of flexibility options, such as heat storage, smart charging of electric vehicles, and demand response. Third, the development of the hydrogen market remains highly uncertain. Our sensitivity analysis could be expanded to assess the impact of varying hydrogen demand levels, PtG capacity, and hydrogen imports on storage requirements and their interactions.

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Declaration of interest

Authors hereby declare that they have no conflicts of interest to disclose regarding the content presented in this paper.

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Appendix A. Model equations

Appendix A.1. Nomenclature

Name	Description	Units
Sets		
gen	Generating technologies (except solar and wind)	
$disp$	Dispatchable generating technologies	
str	Storage technologies	
$w \in [\![1, 52]\!]$	Weeks	
$h \in [\![1, 168]\!]$	Hours of the week	
Stochastic Variables		
$\xi_{pv,w,h}$	Electricity production from solar	GWh
$\xi_{wind,w,h}$	Electricity production from wind	GWh
$\xi^{E}_{dem,w,h}$	Electricity demand	GWh
State Variables		
$l_{str,w,h}$	Filling levels of storage *str*	GWh
Decision Variables		
k^{new}_{str}	New installed capacity of storage *str*	GW
$q_{gen,w,h}$	Generating power of technology *gen*	GWh
$u^{out/in}_{str,w,h}$	Discharging (out) or charging (in) storage *str*	GWh
$q^{E}_{exp,w,h}$	Electricity exports	GWh
$q^{E/H}_{imp,w,h}$	Electricity (E) and Hydrogen (H) imports	GWh
$f^{E/H}_{w,h}$	unsatisfied demand for electricity (E) and hydrogen (H)	GWh
Parameters		
K^{ini}_{gen}	Installed capacity of technology *gen*	GW
K^{ini}_{str}	Initial charging/discharging capacity of storage *str*	GW
K^{E}_{imp}	Maximum electricity import capacity	GW
K^{H}_{imp}	Maximum hydrogen import capacity	GW
K^{E}_{exp}	Maximum electricity export capacity	GW
$W_{river,w,h}$	Energy supplied by water flow to run-off-river plants	GWh
δ_{disp}	Derating factor of technology *disp*	
τ_{str}	Energy/Power ratio of storage *str*	h
$\gamma_{gen/str}$	Efficiency of technology *gen/str*	
$n^{max}_{cyclcing}$	Maximum number of charging cycles allowed per year for UHS storage	
e^{comp}_{UHS}	Hydrogen compressors' electricity consumption	
C^{vOM}_{gen}	Variable cost of generating technology *gen*	EUR/MWh
C^{in}_{str}	Storage injection cost	EUR/MWh
$C^{E/H}_{imp}$	marginal cost of electricity / hydrogen imports	EUR/MWh
C^{E}_{exp}	marginal revenue from electricity exports	EUR/MWh
$VoLL$	Value of Loss Load	EUR/MWh
C^{inv}_{str}	Investment cost of newly installed storage capacities	EUR/MW
C^{fOM}_{str}	Fixed cost of newly installed storage capacities	EUR/MW
$D^{H}_{w,h}$	Hydrogen demand	GWh
ρ^{SMR}	CO_2 emission of SMR	tCO_2/GW
θ	Efficiency rate of CCS	

Appendix A.2. Equations

Cost transition function

The cost transition function of week w is noted C_w. It accounts for the variable costs of running the power and hydrogen-generating technologies needed to ensure supply-demand adequacy at every hour of the week. Generating plants run at C^{vOM}_{gen}, storage injection costs are C^{in}_{str}, and the import and export costs are denoted C_{imp} and C_{exp}. The VoLL penalizes any supply-demand inadequacy. The cost transition function is detailed in equation (A.1).

$$\begin{aligned} C_w = \sum_{h\in(1,\dots,168)} \Bigg[& \sum_{gen} C^{vOM}_{gen} \cdot q_{gen,w,h} + \mathbb{1}_{w=1} \sum_{str} (C^{inv}_{str} + C^{fOM}_{str}) \cdot k^{new}_{str} \\ & + \sum_{str} C^{in}_{str} \cdot u^{in}_{str,w,h} + C^{E}_{imp} \cdot q^{E}_{imp,w,h} - C^{E}_{exp} \cdot q^{E}_{exp,w,h} \\ & + C^{H}_{imp} \cdot q^{H}_{imp,w,h} + VoLL^{E}_{w,h} \cdot f^{E}_{w,h} + VoLL^{H}_{w,h} \cdot f^{H}_{w,h} \Bigg] \end{aligned} \quad \text{(A.1)}$$

Note that the cost function of the first week of the year — characterized by the indicator function $\mathbb{1}_{w=1}$ — includes the annualized investment costs ($C^{inv}_{str} \cdot k^{new}_{str}$) and the fixed costs ($c^{fOM}_{str} \cdot k^{new}_{str}$) of the newly installed storage capacity.

Modeling of the uncertainty

Our solving approach requires discretizing the distribution function for the random variables: at each stage, random variables must take values from a finite and predefined set. In our case, at the beginning of each week w, $\xi_{pv,w,h}$, $\xi_{wind,w,h}$, and $\xi^{E}_{dem,w,h}$ take values from finite and predefined sets denoted $\Omega_{pv,w}$, $\Omega_{wind,w}$, and $\Omega^{E}_{dem,w}$, each composed of five vectors of length 168. These five potential realizations are extracted from historical data. For example, at a given stage w, VRE generation and demand time series for the w^{th} week of the year are selected from five past actual vectors of production or demand for that specific week.

Constraints on electricity generation and hydrogen production

Each dispatchable technology *disp* (gas-fired plants, biomass, hydrogen turbines, PtG, and SMR) is bounded by its available capacity, given by the product of its overall installed capacity K^{ini}_{disp} and its derating factor δ_{disp}, which accounts for the mean availability rate over the year. The hourly run-of-river (RoR) electricity generation is fixed and equal to the energy supplied by the hourly flow of water $W_{river,w,h}$.

$$\forall disp, w, h \quad q_{disp,w,h} \leq K^{ini}_{disp} \cdot \delta_{disp} \quad \text{(A.2)}$$

$$\forall w, h, \quad q_{RoR,w,h} = W_{river,w,h} \quad \text{(A.3)}$$

Restrictions (A.4-A.6) imply that imports and exports of electricity and hydrogen are constrained by interconnection capacity.

$$\forall w, h \quad q^{E}_{exp,w,h} \leq K^{E}_{exp} \tag{A.4}$$

$$\forall w, h \quad q^{E}_{imp,w,h} \leq K^{E}_{imp} \tag{A.5}$$

$$\forall w, h \quad q^{H}_{imp,w,h} \leq K^{H}_{imp} \tag{A.6}$$

Constraints on electricity and hydrogen storage

For each storage *str*, constraints (A.7) - (A.8) impose an upper limit on charging and discharging decisions. The energy stored is limited by the storage capacity, equal to the product of the charging/discharging capacity and the energy-to-power ratio τ_{str}.

$$\forall str, w, h \quad u^{out}_{str,w,h} \leq (k^{new}_{str} + K^{ini}_{str}) \tag{A.7}$$

$$\forall str, w, h \quad u^{in}_{str,w,h} \leq (k^{new}_{str} + K^{ini}_{str}) \tag{A.8}$$

$$\forall str, w, h \quad l_{str,w,h} \leq (k^{new}_{str} + K^{ini}_{str}) \cdot \tau_{str} \tag{A.9}$$

Additionally, we incorporate a constraint limiting UHS to undergo no more than a dozen switches from charging to discharging mode per year, in line with the literature on salt caverns' technical properties (Guidehouse, 2021). To avoid computational issues, we propose a linearization of the cycling constraint in equation (A.10), where $n^{max}_{cycling}$ is the number of cycles allowed per year. This linearization approximates the true non-convex problem very well when the number of UHS facilities exceeds a dozen, which is the case in our results (Blanchard and Massol, 2025).[4]

$$\sum_{w,h} u^{out}_{str,w,h} \leq n^{max}_{cycling} \cdot (k^{new}_{UHS} + K^{ini}_{UHS}) \tag{A.10}$$

Additionally, the filling level at a given hour ($l_{str,w,h}$) is linked to the following one ($l_{str,w,h+1}$) by state transition equations (A.11-A.12) that ensure energy conservation. γ_{str} denotes the round trip efficiency of storage *str*. Equation (A.13) is a closure constraint that requires the energy in storage at the end of the year to be equal to that present at the beginning of the year (set at January 1). In addition, we set the reservoir level at the beginning of the year at half its storage

[4] A typical salt cavern stores in the magnitude of 100GWh of hydrogen. As our model invests in over 5,300GWh of UHS in the base case, it represents about 45 caverns.

capacity.

$$\forall str, w, h \in (1, \ldots, 167), \quad l_{str,w,h+1} = l_{str,w,h} - u^{out}_{str,w,h} + \gamma_{str} \cdot u^{in}_{str,w,h} \tag{A.11}$$

$$\forall str, w \in (1, \ldots, 51), \quad l_{str,w+1,1} = l_{str,w,168} - u^{out}_{str,w,168} + \gamma_{str} \cdot u^{in}_{str,w,168} \tag{A.12}$$

$$\forall str, \quad l_{str,1,1} = l_{str,52,168} \tag{A.13}$$

Finally, current gas networks rely on the flexibility provided by the transmission infrastructure to supply energy in the amount needed at consumption nodes. This capability of the pipelines to bridge short-term demand fluctuations with production or storage releases is known as linepack flexibility (Wilson and Rowley, 2019). We model this to account for the fact that, even though UHS is constrained on output flow rate, hydrogen turbines can consume hydrogen up to their nameplate capacity for several hours, using linepack as a short-term buffer. We model the linepack as an additional hydrogen storage with a low energy-power ratio of 3h, which allows a high production level from hydrogen turbines for a limited amount of time even though UHS output is theoretically not high enough to provide this flow rate of molecules. In the model, the amount of hydrogen discharge from UHS is equal to the amount of hydrogen fed into the linepack:

$$\forall w, h, \quad u^{out}_{UHS,w,h} = u^{in}_{linepack,w,h} \tag{A.14}$$

Supply-demand Adequacy

We implement a supply-demand adequacy constraint for each commodity as we study a combined electric and hydrogen system. Condition (A.15) enforces the electricity supply to equal demand at every hour:

$$\begin{aligned} \forall w, h \quad & \sum_{gen} q^E_{gen,w,h} + \xi_{pv,w,h} + \xi_{wind,w,h} + \sum_{str} u^{E,out}_{str,w,h} + q^E_{imp,w,h} + f^E_{w,h} \\ & = \xi^E_{dem,w,h} + \frac{q^H_{PtG,w,h}}{\gamma_{PtG}} + (u^{in}_{UHS,w,h} + u^{out}_{UHS,w,h}) \cdot e^{comp}_{UHS} \\ & + \sum_{str} u^{E,in}_{str,w,h} + q^E_{exp,w,h} \end{aligned} \tag{A.15}$$

On the supply side, $\sum_{gen} q^E_{gen,w,h} + \xi_{pv,w,h} + \xi_{wind,w,h}$ is the electricity produced from electricity generating technologies, $\sum_{str} u^{E,out}_{str,w,h}$ the electricity discharged from storage, $q^E_{imp,w,h}$ the electricity imported from neighboring grids, and $f^E_{w,h}$ the unsupplied electricity. On the demand side, $\xi^E_{dem,w,h}$ is the exogenous electricity demand, $q_{PtG,w,h}/\gamma_{PtG}$ the electricity used for hydrogen production, $(u^{in}_{UHS,w,h} + u^{out}_{UHS,w,h}) \cdot e^{comp}_{UHS}$ the electricity consumption of the UHS compressors when activated, $\sum_{str} u^{E,out}_{s,w,h}$ the electricity charged into electricity storage, and $q^{E}_{exp,w,h}$ the electricity exported. γ_{PtG} denotes the efficiency of PtG conversion.

In the hydrogen market, condition (A.16) guarantees that the total hydrogen demand equals the total hydrogen supply:

$$\forall w,h \quad \sum_{gen} q^{H}_{gen,w,h} + u^{H,out}_{linepack,w,h} + q^{H}_{imp,w,h} + f^{H}_{w,h} = D^{H}_{w,h} + \frac{q_{HT,w,h}}{\gamma_{HT}} + u^{H,in}_{UHS,w,h} \tag{A.16}$$

On the supply side, $\sum_{gen} q^{H}_{gen,w,h}$ is the hydrogen produced from hydrogen generating technologies (SMR or PtG), $u^{H,out}_{linepack,w,h}$ the hydrogen discharged from storage, $q^{H}_{imp,w,h}$ the imported hydrogen, and $f^{H}w,h$ the unsupplied hydrogen. On the demand side, $D^{H}_{w,h}$ is the exogenous hydrogen demand, $\frac{q_{HT,w,h}}{\gamma_{HT}}$ the hydrogen used for power generation, and $u^{H,in}_{UHS,w,h}$ the hydrogen injected into storage. γ_{HT} denotes the efficiency of hydrogen turbines.

Appendix B. Model parametrization

Assumptions on generation and storage technologies

Table B.2 details capacity, cost, and efficiency assumptions for generation technologies. Electricity generation and PtG capacities are taken from Agora Energiewende report (Energiewende, 2022). We consider two types of gas turbines: CCGT and OCGT. Each type is clustered into three efficiency steps based on the current German generation fleet from (Deloitte, 2019). For SMR capacity, since gas-based hydrogen is considered a transitional option, we assume no additional SMR capacity will be installed until 2035. Instead, we maintain the existing installed capacity of 2.5GW and assume that this technology is enhanced by implementing carbon capture and storage (CCS). Assumptions on derating factors are derived from (Villavicencio, 2017). VoLL is set at EUR 10,000/MWh for electricity and hydrogen.

Table B.3 describes capacity and technical assumptions for storage technologies. UHS and BESS capacities are either optimized by the model (see section 2.4). The linepack discharging capacity is set at 30GW. PHS discharging capacity and PHS and BESS energy-to-power ratio τ_{str} are based on Agora Energiewende's assumptions (Energiewende, 2022). UHS energy-to-power ratio is derived from (Bünger et al., 2017). Round-trip efficiency γ_{str} are taken from (Shirizadeh and Quirion, 2023) for PHS, BESS, and UHS. Linepack's energy-to-power ratio and efficiency are personal assumptions. The remaining technical parameters are detailed in B.4. PtG and SMR parameters are from (Li and Mulder, 2021; Megy and Massol, 2023) and UHS parameters are from (Guidehouse, 2021; Michalski et al., 2017).

Technology	Installed capacities (GW)	Derating factor -	Variable cost (EUR/MWh)
Solar	309	*variable*	0
Wind Onshore	157	*variable*	0
Wind Offshore	58	*variable*	0
Biomass	6	1	50
CCGT_V1	7	0.88	74
CCGT_V2	7	0.88	94
CCGT_V3	7	0.88	110
OCGT_V1	7	0.94	125
OCGT_V2	7	0.94	136
OCGT_V3	7	0.94	149
Hydrogen turbines	20	0.88	*endogenous*
PtG	12	1	*endogenous*
SMR	2.5	1	66

Table B.2: Capacity, cost and efficiency assumptions for generating technologies

Technology	Charging / Discharging capacity (GW)	Energy-Power ratio (h)	Round Trip efficiency
PHS	7	8	0.8
BESS	*endogenous*	4	0.9
UHS	*endogenous*	300	0.98
Linepack	30	3	1

Table B.3: Capacity and technical assumptions for storage assets

Table B.4: Technical parameters

Parameter	Value	Unit
PtG conversion efficiency	0.7	
Hydrogen turbine efficiency	0.6	
SMR conversion efficiency	0.6	
Maximum number of cycles per year for UHS	12	
Electricity consumption of UHS compressors	0.03	$(kWhe/kWh\ H2)$

Assumptions on VRE and demand patterns

The energy supplied by water inflows to run-of-river plants is derived from the 2019 hourly time series (ENTSOE-e transparency platform). As described in Section Appendix A, random variables take their value in a set of five years of wind generation, solar generation, and electricity demand. These alternatives are sampled from 2016-2022 data,[5] scaled up to the projected evolution of both VRE installed capacity and demand trends for 2035. Electricity demand (excluding the electricity required for hydrogen production, which is endogenous in our model) is assumed to reach 773 TWh in 2035 in a net-zero scenario (Energiewende, 2022). For hydrogen demand, we assume a total annual demand of 87 TWh, in line with the German National Hydrogen Strategy (German Federal Government, 2020). Hourly hydrogen demand is assumed to be constant over the year.

Assumptions on electricity and hydrogen cross-border exchanges

Table B.5 details our electricity and hydrogen cross-border exchange assumptions. We assume an electricity export and import capacity of 44 GW, in line with ENTSOe's forecasts for expanding the European transmission network (ENTSOE, 2023). According to a study conducted by the French TSO RTE, the contribution of interconnections in periods of electricity shortage or surplus will decrease over the coming decades due to the evolution of the European power system (RTE, 2021). Following this study, we assume that 70% of electricity exporting and importing capacities are available for cross-border exchanges. The cost of electricity imports is set at the average price level of imported electricity paid in Germany in 2018, which is EUR 55/MWh. Similarly, electricity exports are modeled with a fixed price level of EUR 42/MWh (Bundesnetzagentur, 2019).

Regarding hydrogen imports, the specific quantity of hydrogen to be imported and the corresponding costs of these imports remain uncertain. To model them, we assume a total hydrogen import capacity of 8GW and propose a diversification strategy that allows for the purchase of hydrogen from 7 distinct sources, each with an equivalent capacity of 1.14GW. The prices of these hydrogen clusters range from EUR 3-8/kg H_2 (EUR 91-242/MWh), in line with recent studies' projections (Guidehouse, 2021; Van Wijk and Chatzimarkakis, 2020).

	Capacity (GW)	Derating Factor	Cost (EUR/MWh)
Electricity export	44	0.7	42
Electricity import	44	0.7	55
Hydrogen import	8	-	21-242

Table B.5: Assumptions on import and export capacity and cost

[5] Excluding 2020 and 2021, data extracted from the ENTSOe transparency platform

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