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The Cost of Security: Analyzing Strategies to Hedge Hydrogen Import Disruption under Stochastic Representation of Weather

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Abstract

The European Union's pursuit of climate neutrality necessitates a robust and secure energy system that will likely become reliant on imported green hydrogen. However, this dependency introduces inherent risks related to import disruptions and the weather-driven production variability of green hydrogen. This paper develops a comprehensive modeling approach to address these risks in a decarbonized European energy system. We use stochastic optimization to account for weather-induced variability, while applying dedicated mitigation strategies to analyze the cost and implications of hedging against import disruptions. We model hydrogen imports via long-term contracts, with prices and delivery profiles determined based on a stochastic calculation of the levelized cost of hydrogen supply. This approach informs the stochastic modeling of the European energy system using the HYEBRID model, which accounts for weather variability across domestic and exporting regions. Our analysis reveals that the stochastic extension of HYEBRID reduces system costs by one-third compared to a deterministic solution that assumes average weather conditions. We also identify the need for a substantial expansion of hydrogen storage capacity, considerably exceeding previous estimates, to manage fluctuations in both domestic and imported supply. a pure cost minimization of imports results in significant market concentration, with only three exporters being contracted. By evaluating strategies to mitigate import disruption risk, we find that diversification and import reduction strategies incur higher costs in the investment stage, which can be economically justified if the perceived risk of exporter disruption is sufficiently high.

Keywords: Energy System Modeling, Hydrogen Infrastructure, Stochastic Optimization, Weather Variability, Hydrogen Import Risks

JEL classification: C61, F52, Q27, Q41, Q42, Q48.

1. Introduction

The European Union's pursuit of climate neutrality necessitates a fundamental shift in energy sourcing and an expanded role for green energy within its system (EC, 2022). This transition increasingly involves the import of diverse renewable energy carriers, with ongoing discussions addressing the optimal mix and scale of such imports (Neumann et al., 2025). Within this evolving energy landscape, imported green hydrogen

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is positioned as a pivotal component of Europe's decarbonization strategy, aiming for climate neutrality by 2050. Ambitious targets include 10 million tonnes of renewable (green) hydrogen imports by 2030, as outlined in the REPowerEU Plan (EC, 2022). Nevertheless, reliance on imported energy commodities inherently introduces risks related to import disruptions and price volatility, as history has repeatedly demonstrated. The European gas crisis of 2022, followed by the Russian invasion of Ukraine, serves as an urgent reminder of the profound economic and social repercussions of overreliance on a limited number of external suppliers (Emiliozzi et al., 2023). While a nascent international hydrogen market is emerging, its initial development may lead to a concentration of supply similar to early natural gas markets (Dejonghe et al., 2023). Future supply chains could be shaped by long-term contracts (Antweiler and Schlund, 2023), infrastructure development (Schlund, 2023; Kountouris et al., 2024a; ENTSOE and ENTSOG, 2025), and geopolitics (Van de Graaf et al., 2020), all of which are subject to considerable uncertainties. Amid growing global geopolitical risks, there are calls for a more independent European energy policy (Herranz-Surralles, 2024), advocating for enhanced domestic production capabilities (EU Parliament & Council, 2024) and a higher degree of self-sufficiency (Jerzyniak, 2024). However, security concerns and risk exposure within emerging hydrogen markets, particularly concerning potential disruptions and market concentration, remain largely underinvestigated.

Although a future international green hydrogen market could offer a pivotal pathway for Europe's decarbonization (EC, 2022), its fundamental reliance on water electrolysis powered by renewable energy sources inherently links global production facilities to weather variability. The Levelized Cost of Hydrogen (LCOH) is a common metric for estimating the supply costs of green hydrogen and its derivatives from diverse regions worldwide, as derived, for example, by Moritz et al. (2023). These studies often identify cost advantages for importing hydrogen to Europe. Nevertheless, the calculations are typically based on single weather years, which can lead to inaccurate revenue and cost projections for exporting facilities. Furthermore, weather variability emerges as a crucial factor for the design and operation of domestic hydrogen production via electrolysis. Despite its importance, current European long-term infrastructure planning, as detailed in the TYNDP reports by ENTSOE and ENTSOG (2022, 2025), often relies on single weather years. Moreover, deterministic approaches with limited consideration of weather variability are commonly employed to assess future European hydrogen infrastructure needs (Neumann et al., 2023; Frischmuth et al., 2024). A profound understanding of weather variability is vital, as investment decisions for a future climate-neutral energy system involve long planning horizons, and such considerations become increasingly relevant amid discussions on enhancing the resilience of European energy systems. While stochastic optimization approaches have been applied within the electricity sector to manage uncertainties, among others (Fürsch et al., 2013; Scott et al., 2021; Möbius et al., 2023), their application to the hydrogen sector remains notably limited. This highlights a critical gap in comprehensive, uncertainty-aware modeling frameworks for an integrated European electricity and hydrogen system that explicitly addresses the multifaceted impact of weather variability.

Against this backdrop, this paper addresses the following research questions: (i) How does the stochastic representation of weather variability impact LCOH estimations? (ii) What is the cost advantage of a stochastic optimization of European electricity and hydrogen infrastructure over a deterministic optimization, and what are the implications for infrastructure investments? (iii) What are the additional costs of hedging against the risk of a potential disruption in hydrogen imports?

To answer these research questions, we extend the work by Moritz et al. (2023) with a stochastic calculation of LCOH and compare the results with deterministically determined LCOH. The LCOH then inform the coupled electricity and hydrogen market model HYEBRID, first introduced in Keutz and Kopp (2025). We extend the HYEBRID model with a stochastic representation of weather and demonstrate its benefit over a deterministic representation of weather using the Value of Stochastic Solution (VSS). This analysis is followed by an evaluation of the resulting energy system configuration and hydrogen import structure. Given the potential for high market concentration in hydrogen imports, we assess mitigation strategies to hedge the risk of a disruption in imports: *diversification*, *reduction of imports*, and a *combined strategy*. Finally, the *cost of security* through mitigation strategies is contextualized by translating the cost premium of full autarky into a perceived disruption probability of exporters, providing a benchmark for policymakers.

By providing a robust, uncertainty-aware modeling framework, this paper offers significant methodological contributions to the energy economics literature. In addition, it provides crucial insights for industry stakeholders, policymakers, and European regulatory authorities. First, it enhances understanding of how weather-dependent hydrogen production in exporting regions and European weather variability could influence long-term contract pricing. Second, it demonstrates how a stochastic treatment of weather uncertainty enables robust investment for the European electricity and hydrogen sectors. We find significant infrastructure shifts such as increased hydrogen storage capacity to manage both domestic and export-side weather variability. Third, it quantifies the *cost of security* for proactive mitigation strategies, introducing an economic benchmark that relates the cost of mitigation to the level of perceived exporter disruption risk required to justify it. Finally, our findings guide policymakers and industry stakeholders in designing robust hydrogen import strategies, informing both infrastructure investment and future contractual frameworks.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 details the LCOH calculation and the extended HYEBRID model, outlining the stochastic methodology for incorporating weather variability and assessing disruption risks, alongside key assumptions. Section 4 presents our findings, beginning with LTC prices and the quantification of the VSS, followed by an analysis of mitigation strategies to hedge the risk of import disruption. Section 5 offers a thorough discussion of our findings, reflecting on assumptions and limitations. Finally, Section 6 concludes the paper.

2. Literature

This work addresses two key streams of literature. The first stream focuses on the optimization of electricity and hydrogen sectors, including critical modeling inputs such as hydrogen import prices. The second stream investigates import risks and resilience in emerging hydrogen markets. This area encompasses historical analyses of energy import disruptions, particularly within the natural gas market.

Several studies investigate the combined optimization of European electricity and hydrogen infrastructure, though each study emphasizes different aspects. High spatial resolution is a key aspect of the work by Neumann et al. (2023), which uses a linear optimization model that spatially resolves European countries into 181 regions to improve the visibility of within-country infrastructure investments. Further studies focus on the intertwined development of hydrogen networks and electricity transmission expansion across Europe (Neumann et al., 2025; Frischmuth et al., 2024). Neumann et al. (2025)

specifically analyze varying import scenarios by coupling global and European energy system models, underscoring the potential for system cost reductions through coordinated import strategies. Keutz and Kopp (2025) investigate the impact of Take-or-Pay (TOP) obligations on infrastructure investment and system dispatch under different weather conditions, revealing the sensitivity of cost-optimal infrastructure and reliability to TOP rates. Frischmuth et al. (2024) quantify hydrogen infrastructure development using pan-European energy system (SCOPE SD) and gas market (IMAGINE) models, highlighting the influence of storage costs and market uptake on storage demands and the necessity for substantial infrastructure expansion beyond repurposed methane pipelines. Complementing these model-based analyses, Schlund (2023) adopts a scenario-based approach to examine the interdependencies of energy system elements for hydrogen integration into existing gas infrastructure. Long-term infrastructure projections, such as the TYNDPs 2022 and 2024 by ENTSOE and ENTSOG (2022, 2025) or the Long-term Scenarios 3 by Sensfuß et al. (2024), also model energy system investment and dispatch to project cost-efficient infrastructure needs and viable hydrogen import volumes. However, a common limitation in these analyses is the frequent use of deterministic optimization.

Stochastic approaches have been applied to electricity system modeling to address uncertainties. For example, Möbius et al. (2023) analyze the impact of risk aversion on investment strategies using a stochastic transmission and generation expansion model. Scott et al. (2021) examine the effects of different uncertainty sources on generation expansion planning, while Fürsch et al. (2013) use a linear multi-stage stochastic investment and dispatch model to analyze the effects of uncertain renewable energy deployment. Riepin et al. (2021) quantify the value of encoding the uncertainty of input parameters, finding that the expected costs of ignoring uncertainty can constitute up to 20% of cumulative costs from investments in power generation capacity.

The application of stochastic approaches to the hydrogen sector remains limited, often focusing on national or regional levels and specific supply chains. Examples include Almansoori and Shah (2012), who model a stochastic hydrogen supply chain network for Great Britain under demand uncertainty; Türkali Özbek and Güler (2025), who develop a multi-objective stochastic model for hydrogen supply chain planning in Turkey; Kim et al. (2008), who design hydrogen supply chains under uncertain demand in Korea; and Ochoa Bique et al. (2021), who employ a scenario tree for a multi-stage stochastic programming model to address hydrogen demand uncertainty in Germany. In light of the limited application to the European scale, this paper expands the capabilities of the HYEBRID model by integrating a stochastic approach into a European electricity and hydrogen investment and dispatch model.

The second key stream of literature investigates prices, risks, and resilience aspects surrounding hydrogen imports. LCOH often serve as a reference point for future hydrogen prices. A significant body of literature defines and calculates LCOH for various hydrogen supply chains, with recent studies expanding on global potentials and cost drivers. For instance, Moritz et al. (2023) conduct a techno-economic analysis to estimate global production and supply costs for green hydrogen and various hydrogen-based energy commodities in 113 countries, building upon the work of Brändle et al. (2021). Further comprehensive analyses, such as the Fraunhofer IEE PtX-Atlas by Pfennig et al. (2021) and the work by Franzmann et al. (2023), also present global LCOH estimations. They provide detailed cost-potential curves, often considering the full process chain for hydrogen export. Radner et al. (2024) analyze off-grid hydrogen production and supply costs to Europe, incorporating country-specific investment risks and transport. Additionally, studies by Mendler et al. (2024) and Kigle et al. (2024) explore methodologies to optimize capacity ratios and analyze the impact of country-specific investment risks on LCOH. However, LCOH calculations usually rely on a single or limited selection of historical weather years, overlooking the significant impact of inter-annual weather variability on the operational performance and cost-effectiveness of hydrogen production. This can lead to LCOH that do not reflect potential deviations in generation under a broader range of weather conditions.

Lessons from natural gas market disruptions offer valuable insights into potential geopolitical risks for future hydrogen markets. The European energy crisis of 2022, triggered by Russia's weaponization of natural gas supplies, serves as a highly relevant example. The curtailment led to unprecedented price surges across European markets, necessitated a significant reduction in gas consumption, and fundamentally reshaped global LNG trade as Europe sought alternative supplies (Emiliozzi et al., 2023). In response, the EU swiftly transformed its energy policy; for instance, the REPowerEU plan focused on diversifying gas supplies away from Russia and accelerating the transition to renewables (Lambert et al., 2022; Calanter and Zisu, 2022). Research has also investigated operational aspects, with studies on diversification strategies to foster resilience (Hauser, 2021) and analyses of collaborative versus selfish behavior during energy scarcity (Mannhardt et al., 2023). These works identify adaptation strategies, including diversifying imports, shifting to non-gas generation, and reducing demand.

The insights from the 2022 gas crisis regarding supply security, price volatility, and the imperative of diversification and collaborative action offer valuable lessons for the nascent international hydrogen market. However, research targeting risks related to international hydrogen trade remains notably limited.

Existing studies on hydrogen trade risks identify factors such as high investment costs for production and delivery technology, insufficient electrolyzer capacity, and policy or regulatory challenges in Europe (Azadnia et al., 2023). Notably, some analyses of "supplier failure" primarily concern material suppliers rather than geopolitical risks affecting hydrogen imports. Dejonghe et al. (2023) examine whether future hydrogen imports enhance EU energy security or perpetuate vulnerabilities, drawing lessons from historical natural gas trade in Northwest Europe. They suggest that policy-driven market development could lead to a less unified and concentrated market, potentially reducing supply disruption risks. Targeting policymakers, Ansari and Pepe (2023) identify criteria for selecting trade partners and crafting trade frameworks. Moreover, strategies, such as Germany's 2024 hydrogen import strategy (The Federal Government of Germany, 2024), emphasize resilient imports through diversification, broad export origins, and parallel import infrastructure. Furthermore, Nuñez-Jimenez and De Blasio (2022) analyze three strategic scenarios for the European Union's renewable hydrogen market (Hydrogen Independence, Regional Imports, and Long-Distance Imports), finding that long-distance imports offer supply diversification and enhanced security without substantially increasing costs.

3. Methodology

This section outlines the methodological framework. We describe the stochastic extension made to the HYEBRID model, including the disaggregation of hydrogen exporters. Furthermore, we describe our stochastic approach for determining hydrogen import prices based on LCOH and the selection of weather years. Finally, we present the scenarios employed to investigate strategic approaches to hydrogen import contracting, followed by a summary of the key assumptions and data sources that parameterize our model.

Our methodological framework consists of a two-step approach, as visualized in Figure 1. This approach is designed to manage weather variability through stochastic optimization in exporting countries (step I), followed by European countries within the scope of the HYEBRID model (step II). In step I, we first stochastically calculate the LCOH for multiple exporters, optimizing their production assets under inter-annual weather variability to determine robust LTC prices (detailed in Section 3.2). These fixed LTC prices are then used as inputs for the HYEBRID model in step II. Here, we conduct a stochastic optimization of the European electricity and hydrogen system to determine the cost-optimal system design and operation under various risk mitigation strategies (detailed in Sections 3.1 and 3.5).

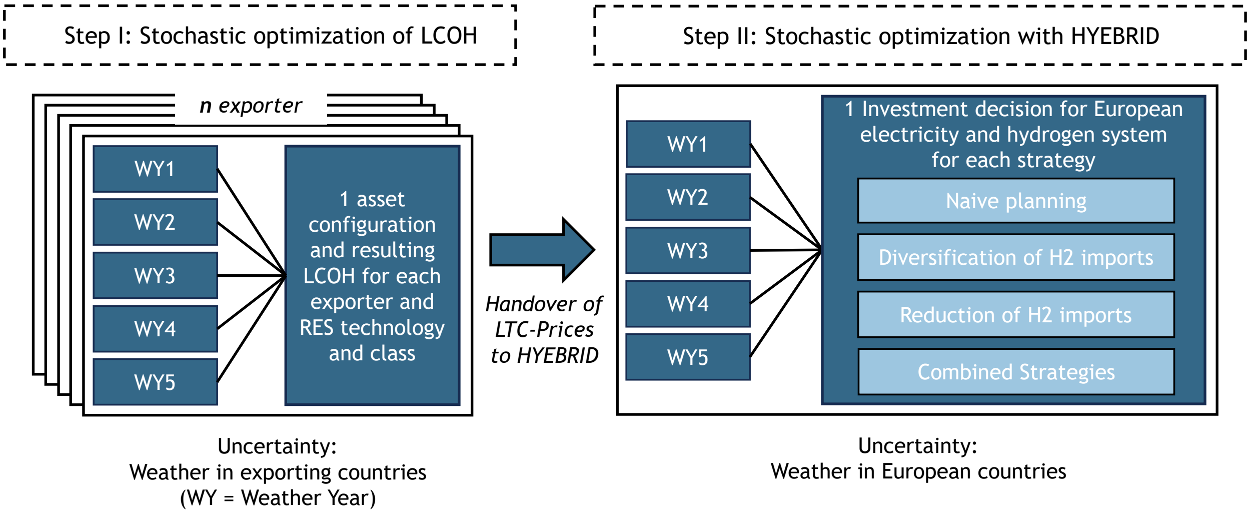

Figure (1) Overview of the two-step stochastic modeling approach

3.1. Stochastic model of European electricity and hydrogen system

Our methodological approach is based on the coupled electricity and hydrogen market model HYEBRID, first introduced in Keutz and Kopp (2025). For this analysis, we extend the model in two key ways. First, we disaggregate hydrogen exports to Europe from a single virtual exporter into multiple exporters, each characterized by individual cost structures and quantities. Second, we introduce inter-annual weather variability directly into the investment stage of the model through a stochastic approach. Figure 2 illustrates the overall model structure, including the upstream determination of LTC prices (detailed in Section 3.2) and the subsequent optimization of the European energy system that incorporates these prices.

Existing research has shown that relying on single weather years in modeling investment decisions can result in lower reliability of the energy system (Keutz and Kopp, 2025; Ruhnau and Qvist, 2022). To overcome this, we incorporate multiple weather years with a stochastic approach, capturing the inherent uncertainty induced by weather variability. The approach used in this work is a linear two-stage stochastic program, similar to Möbius et al. (2023) and based on the general formulation as described in Birge and Louveaux (2011). The rationale behind this formulation is that first-stage (investment) decisions must be made before the uncertainty in risk-related parameters is resolved. The first-stage problem minimizes investment costs and the expected costs of the second stage. In our case, the second-stage uncertainty stems from the impact of weather on both supply and demand. This uncertainty is represented through a

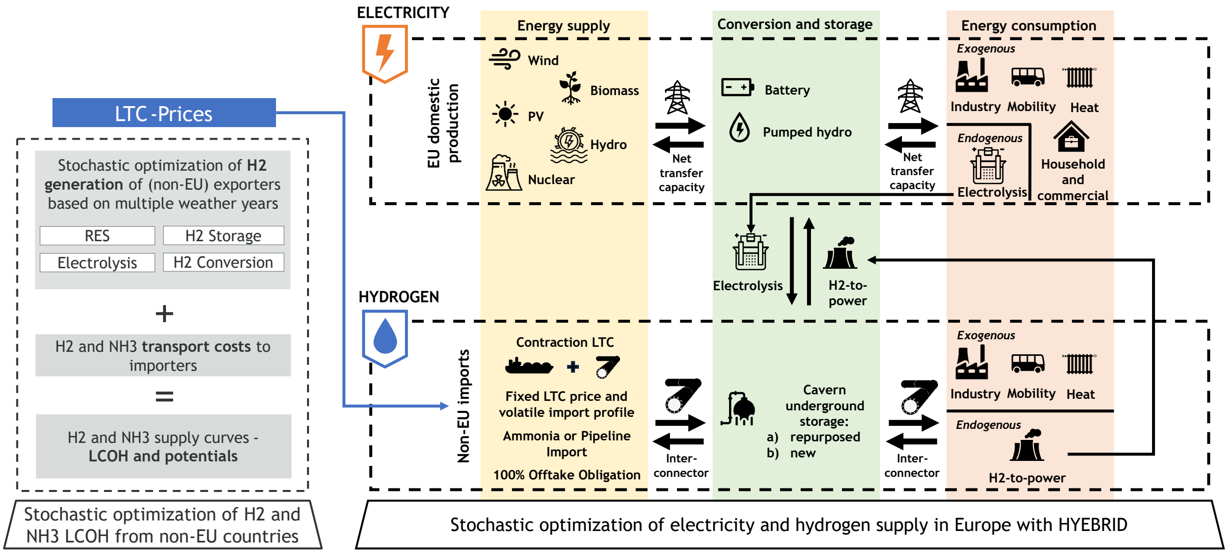

Figure (2) Schematic model overview: stochastic determination of LTC prices and European energy system

set of discrete weather scenarios, each associated with a specific probability. In the second stage, the uncertainty is considered resolved, and the optimal dispatch of assets is determined for each scenario, ensuring feasibility across all realizations of weather. Both first- and second-stage decisions are solved jointly within a single optimization framework. It is important to note that the model represents a long-run equilibrium, in which the probability-weighted weather scenarios are assumed to accurately reflect the long-term variability of actual weather conditions. Consequently, the stochastic programming approach captures the expected distribution of outcomes across multiple representative years, rather than simulating real-time uncertainty. In this sense, the formulation resembles a probability-weighted multi-year linear program, focusing on an equilibrium-consistent representation of weather variability over short-term stochastic risk.

This section presents key changes to the deterministic model formulation of HYEBRID, first outlined in Keutz and Kopp (2025). The total cost function (Equation 1) minimizes fixed costs for operation and maintenance FOM and annualized fixed costs AFC for all technologies $tech$ at each node n. These costs can be associated with the first-stage problem. The second-stage costs comprise variable costs $OPEX$ and costs for hydrogen imports from non-European countries IC, which are calculated for each scenario s. Our setting assumes risk-neutrality, and therefore, we minimize the expected value of total costs. The expected value of second-stage costs per scenario is calculated by multiplying these costs by the probability of each scenario p_s. The sum of all scenario probabilities is one.

$$\begin{aligned} min\ TC = &\sum_{n,tech} (FOM_{n,tech} + AFC_{n,tech}) + \\ &\sum_{d,h,n,tech,s} OPEX_{d,h,n,tech,s} \cdot p_s + \sum_{d,n,s} IC^{H2}_{d,n,s} \cdot p_s \end{aligned} \tag{1}$$

All equations that include second-stage variables are formulated for every scenario individually. In equation 2 we exemplify the adjustment with the equilibrium constraint of electricity. $S^{EL}_{d,h,n,tech,s}$ is the electricity supply by a technology $tech$ to a node n at day d and hour h in scenario s, $d^{EL,exo}$ is the exogenous electricity demand, $D^{EL,H2}$ is the endogenous electricity demand by electrolysis, $TRADEBAL^{EL}$ is the electricity trade balance, and L^{EL} represents uncovered electricity demand.

$$\sum_{tech}(S^{EL}_{d,h,n,tech,s} - S^{EL}_{d,h,tech,n,s}) = d^{EL,exo}_{d,h,n,s} + D^{EL,H2}_{d,n,s} - TRADEBAL^{EL}_{d,h,n,s} - L^{EL}_{d,h,n,s} \;\; \forall d, h, n, s \tag{2}$$

Second-stage variables are generally constrained by first-stage variables, which creates a link between the two stages. This applies to all capacity variables, e.g., renewable capacity, storage volume, or transmission capacity. We exemplify this relationship with the domestic generation of hydrogen, which is constrained by electrolysis capacity in Equation 3.

$$S^{H2}_{d,n,tech,s} \leq C^{H2,ELY}_{n} \;\; \forall d, n, tech, s \in Tech^{\mathrm{H2,ELY}} \tag{3}$$

Unlike the initial formulation of HYEBRID, we do not account for explicit investments in hydrogen terminal capacity. Instead, import infrastructure costs are included in the LCOH and differentiated between imports via ship and pipeline (see Section 3.2 for further explanation). Moreover, we assume a take-or-pay rate of 100%; that is, the total annual volume of the contracted LTC has to be imported or financially compensated. The import costs IC are calculated as the LCOH of each export route e multiplied by the imported quantity I (Equation 4).

$$IC^{H2}_{d,n,s} = \sum_{e} lcoh_{e} \cdot I^{H2}_{d,n,s} \;\; \forall d, n, s \tag{4}$$

Although the import quantity is a second-stage variable, its volume is determined by a first-stage variable. In the first stage, importers decide on an LTC with a predefined *profile* for hydrogen deliveries. The decision variable $LTCS$ determines the contracted share of an exporter's total export potential *expot*, and thus, the quantity and temporal structure of imports I. This rationale is reflected in Equation 5.

$$I^{H2}_{d,n,s} = \sum_{e} LTCS_{n,e} \cdot profile^{H2}_{d,e,s} \cdot expot_{e} \;\; \forall d, n, s \tag{5}$$

In summary, our model formulation simulates the optimal allocation of resources, encompassing long-term investment decisions, the contracting of long-term hydrogen contracts, and dispatch decisions, all co-optimized under uncertain weather conditions.

3.2. Stochastic model of hydrogen import prices

In determining the cost-minimal European energy system configuration, we rely on assumptions for the prices of hydrogen LTCs, using the LCOH as a reference. A comprehensive approach to calculate the LCOH of various potential exporters worldwide was first developed in Brändle et al. (2021), which has since been used as a benchmark for import costs in numerous other publications, including the TYNDP 2024 (ENTSOE and ENTSOG, 2025). Our assumptions for the calculation of LCOH are specifically based on Moritz et al. (2023), who extend the methodology initially presented in Brändle et al. (2021). Their methodology optimizes asset combinations (e.g., PV and electrolysis) by dividing their total costs by the anticipated hydrogen output over their operational lifetimes, yielding the levelized cost of hydrogen generation. This generation cost is then combined with the levelized costs of various transport methods (pipeline, ship) and routes from each exporter to each potential importer, determined based on distances. Together, these components result in the LCOH for each combination of exporter, importer, renewable energy class and resource, and transport method.

However, Moritz et al. (2023) calculate expected output based on a single weather year. This approach is insufficient for our analysis, as the contracting of LTCs within HYEBRID is determined under significant weather uncertainty. Weather characteristics not only influence demand and supply within Europe but also crucially impact the availability and output of non-European hydrogen supply, directly affecting the LCOH. Against this background, we adjust the deterministic linear optimization used in Moritz et al. (2023) by implementing a stochastic linear optimization of assets that incorporates multiple weather years.

Similar to the approach detailed in Section 3.1, the formulation of all second-stage (dispatch) variables in the calculation of LCOH is extended to account for distinct scenarios. Again, these scenarios contain information on the realization of individual weather years. The total cost functions, as originally defined in Moritz et al. (2023) (Equations A.3 and A.4) remain unchanged, as only the capacity-related first-stage variables are included in the objective function. The first-stage capacity decision restricts the second-stage variables. Specifically, Equation 6 ensures that hydrogen production in every weather year s, hour h, resource class r, and at node n for the combination of res technology and electrolysis res,el is constrained by the renewable technology capacity C and time-dependent capacity factor cf. The methodology for calculating these capacity factors is described in Appendix A. Correspondingly, Equation 7 restricts the hourly hydrogen output by the electrolysis capacity. Lastly, Equation 8 ensures that the hydrogen demand d is met. For this calculation, we parameterize the demand such that a mean output of one kilogram of hydrogen per hour must be produced.

$$Q^{res,el}_{n,r,h,s} \leq C^{res}_{n,r} \cdot cf^{res}_{n,r,h,s} \cdot \eta^{el}_{y} \quad \forall n, r, h, s \tag{6}$$

$$Q^{res,el}_{n,r,h,s} \leq C^{el}_{n,r} \cdot \eta^{el}_{y} \quad \forall n, r \tag{7}$$

$$\sum_{s} \sum_{h} Q^{res,el}_{n,r,h,s} \cdot p_s = d^{res,el}_{n,r} \quad \forall n, r \tag{8}$$

With the optimal asset composition determined by these constraints, the LCOH for a combination of node n and renewable technology r is calculated. This is achieved by multiplying the total cost of the optimized asset composition by the lower heating value lhv (33.33 kWh/kg), and then dividing this by the total quantity of hydrogen the assets are expected to generate over their operational lifetime (Equation 9).

$$lcoh^{*,cl,res}_{n,r,y} = lhv \cdot \frac{TC^{*,cl,res}_{n,r,y}}{\sum_h \sum_s Q^{*,res,cl}_{n,r,y,h,s}} \tag{9}$$

In this way, the LCOH describe the expected costs of hydrogen production, specifically taking into account the inter-annual weather variability over the lifetime of the assets. In our model framework, we parameterize LTC prices based on the LCOH calculated in Equation 9. As a result, the LTC price is fixed and independent of the weather year. Despite an intermittent quantity, hydrogen exporters face no risk of failing to recover its investment, if actual weather conditions are correctly reflected in the stochastic optimization. We assume that long-run weather conditions are represented within the stochastic investment decision, which guarantees refinancing. This constitutes an approximation, since the variability within the clustered set of representative weather years is lower than the actual variability observed across a broader historical range. In addition, future weather patterns will be affected by climate change, which is not well captured by past data.

We note that the LTC price could alternatively be formulated to depend on scenario s, and adjust to inter-annual output variability to guarantee a constant revenue stream for the exporter in every weather year. However, this formulation would be equivalent to a constant LTC price in optimizing the import decision in the HYEBRID model, since the total import cost for a contracted LTC ($LTCS$) is the same as with a fixed LTC price under a risk-neutral cost optimization.

Figure 3 compares the LCOH resulting from multiple single-year optimizations with the LCOH from a single stochastic optimization that incorporates all of those weather years. The variability in the LCOH for single weather years highlights the inter-annual output variability. The mean LCOH of the single optimizations is a hypothetical case and should not be used for subsequent calculations, as each single-year optimization inherently yields a distinct, specific asset structure optimized only for that particular year's weather. In contrast, the stochastic optimization method generates a single, robust asset structure designed to perform well across all considered weather years.

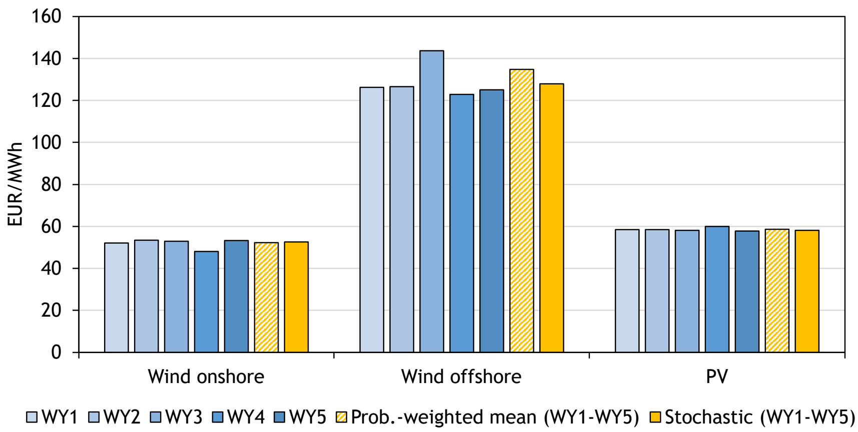

Figure (3) Exemplified LCOH of Morocco (MA) for single year and stochastic optimization in the target year 2050

To further illustrate the impact of this methodological choice, Figure 4 compares the stochastically calculated LCOH with the probability-weighted mean of LCOH values from single-year optimizations. The analysis is shown for 15 potential exporting countries, using exclusively wind onshore potentials for hydrogen production. The stochastic LCOH can be either higher or lower than the probability-weighted mean, depending on the region's specific weather patterns. This demonstrates that a simple deterministic average can be misleading, and the stochastic approach provides a more realistic and reliable cost basis for long-term contracts. For a comprehensive comparison, the results for wind offshore and PV are provided in Figures B1 and B2 in Appendix B.

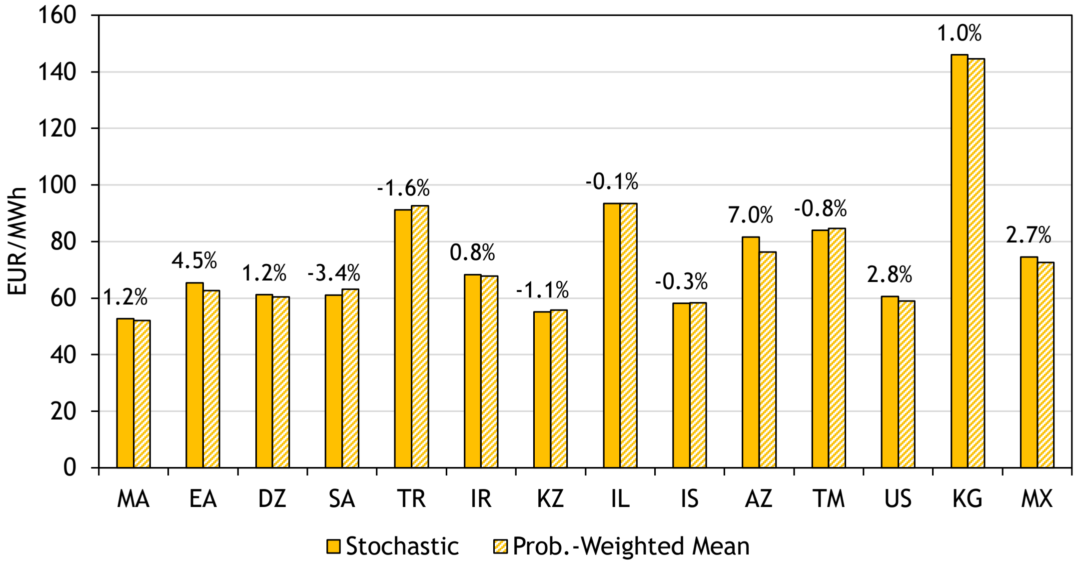

Figure (4) Comparison of stochastic LCOH and probability-weighted mean LCOH for wind onshore across various exporting countries. Percentages indicate the differences between both methodological approaches

3.3. Determination of representative weather years

The computational complexity inherent in the stochastic optimization of the European energy system limits the number of scenarios that can be included. To address this, we reduce a total set of 27 available weather years to a more manageable set of five years using a clustering approach.

Numerous publications apply or develop a clustering of large time-series data to make computation of energy system models feasible. For example, Pfenninger (2017) and Kotzur et al. (2018) show the need to capture extreme events within the clustering process. However, as Hilbers et al. (2019) point out, it is difficult to define before a model run which periods can be considered extreme (a circular situation). Against this background, we cluster our initial set of 27 weather years based on the system costs they imply. Our objective is to select a reduced set of weather years that effectively captures the overall distribution of system costs, including those years that lead to extreme costs.

We run the HYEBRID model for each of these single weather years. This yields a distribution of total system costs, which varies depending on the specific weather characteristics of each year. Figure 5 illustrates the relative deviation of these system costs for each weather year compared to the mean system cost across all 27 years. This analysis demonstrates the sensitivity of the energy system's performance to the unique weather characteristics of each year.

To select the five representative weather years, we employ a hybrid approach combining interval partitioning and representative selection from the distribution of total system costs. The grouping methodology establishes five distinct groups based on cost deviations. The most critical weather year (2010) results in a deviation from the mean system cost of 8%, while the least critical weather year (1995) results in a deviation of -6.4%. These two extreme weather years are highlighted in orange in Figure 5.

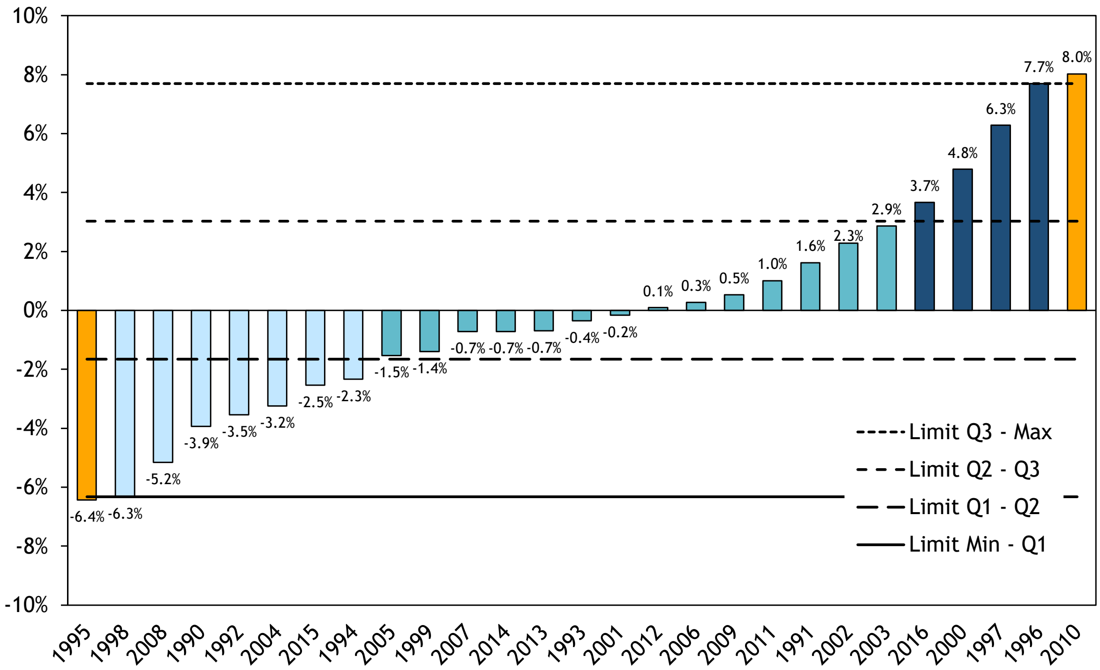

Figure (5) Relative deviation in total system costs of single weather years from the average of 27 weather years computed with the model HYEBRID

The remaining 25 weather years exhibit system cost deviations within this range, which illustrates the spectrum of weather impact on system costs.

The years with the absolute minimum (1995) and maximum (2010) system cost deviations each form a singleton group. The boundaries of the three remaining groups are determined by dividing the range of relative system cost deviation between the second-least critical weather year (1998, -6.3%) and the second-most critical weather year (1996, 7.7%) into three equidistant intervals (approximately 4.7% each). This ensures a relatively even distribution of weather years across the intermediate groups.

The resulting classification of weather years into groups is visually represented by the different colored groups in Figure 5, with the horizontal dashed lines indicating the equidistant limits between each group. From each of these five groups, the representative weather year is selected as the year with the system cost deviation closest to the mean deviation of all weather years within that specific group. This process yields the following representative weather years: Cluster 1: 1995, Cluster 2: 1992, Cluster 3: 2012, Cluster 4: 1997, and Cluster 5: 2010. The representative years, along with their associated probabilities ($\frac{1}{27}$ for 1995 and 2010, $\frac{7}{27}$ for 1992, $\frac{14}{27}$ for 2012, and $\frac{4}{27}$ for 1997), form the basis of the scenario set used in the model HYEBRID and in the calculation of LCOH.

The clustering methodology does not account for whether the correlation of RE yields between the EU and exporting regions is adequately represented in the clustered weather years. Addressing this aspect would require multi-criteria clustering approaches capable of capturing both the variability in RE yields and an accurate representation of their interregional correlation. Nevertheless, Figure C3 in Appendix C presents an ex-post assessment of the correlations and illustrates how effectively the clustering reproduces the relationships observed in the full dataset.

3.4. Assumptions and data

The regional scope of the model encompasses the EU27, the United Kingdom, Norway and Switzerland, excluding Cyprus, Malta, Bulgaria, and Greece. The temporal scope is the year 2050, aligned with the EU's climate-neutrality target. This necessitates a zero-emission power and hydrogen sector within the model framework. The model considers 32 representative days with hourly resolution for each representative weather year. The representative days are identified using k-medoids clustering based on today's residual load (cf. Kotzur et al. (2018)). We allow for electric lost load in the model. The Value of Lost Load (VOLL) varies by region and sector and is highly uncertain (ACER, 2022). Therefore, we set the VOLL to the maximum clearing price of the single day-ahead coupling (ACER, 2023).

The model's technological scope is summarized in Figure 2. A detailed overview of the techno-economic assumptions for the technologies considered in this analysis is provided in Table D1 in the Appendix. All cost data are converted to €$_{2019}$, and calorific units are based on the lower heating value. For the power sector, the model initializes with 2022 capacities for electricity supply, conversion, and storage, allowing for expansion except for nuclear and hydro capacities, which are held constant. Hydrogen can be produced domestically by electrolysis or imported from non-European countries. Assumptions for the costs and temporal structure of hydrogen imports are based on Section 3.2. Hydrogen storage is modeled using repurposed or newly built salt caverns, currently representing the most promising and cost-effective type of long-duration underground hydrogen storage (Caglayan et al., 2020). In the model, storing hydrogen in cavern sites is enabled only in countries[1] with existing and operating caverns for natural gas. Moreover, the model differentiates between storage volume, injection capacity, and withdrawal capacity, as the volume-to-capacity ratio in a climate-neutral energy system may deviate from the current ratios for natural gas storage. To ensure consistency over the modeling period, we prescribe the filling level of hydrogen storage at the end of the year to be equal to that at the start of the year. Hydrogen transmission is modeled using hydrogen interconnectors created by repurposed natural gas pipelines, based on ENTSOG (2023). A repurposing rate of 50% and a conversion factor of 75% of the initial natural gas capacity, derived from Galyas et al. (2023), is assumed.

Annual electricity demand is based on TYNDP's Global Ambition scenario for 2050 (ENTSOE and ENTSOG, 2025). To capture the weather-dependent nature of electricity demand, we use the hourly demand time series from the European Resource Adequacy Assessment (ERAA) 2023 (ENTSO-E, 2023). These time series cover the weather years from 1990 to 2016. We combine the two data sources by multiplying the demand time series from ERAA by the total demand from TYNDP for 2050 for every country. Then, we divide the product by the average total demand across the 27 weather years to normalize the data. Similarly, hydrogen demand follows TYNDP's Global Ambition scenario for 2050 (ENTSOE and ENTSOG, 2025), assuming a flat demand from the end-use sectors of industry and mobility and a temperature-dependent demand from the residential sector (cf. Keutz and Kopp (2025)). Hydrogen demand for electricity reconversion is determined endogenously. The hourly availability of solar

[1] These countries are FR, DE, DK, NL, PL, PT, and GB, following current data from Gas Infrastructure Europe (GIE, 2021).

PV, wind onshore, and wind offshore is derived from ENTSO-E (2023). Run-of-river flows, storage volumes of pumped-hydro units, and weekly hydro reservoir levels are also based on ENTSO-E (2023).

3.5. Scenario framework

Intuitively, a cost optimization favors selecting the most affordable LTCs for hydrogen imports and leverages the potential of the least expensive options until equilibrium with domestic generation is achieved. However, the lessons learned from the gas crisis in 2022 underscore the significant risks of overreliance on a limited number of exporters, including high prices and broader economic repercussions, such as inflation resulting from a sudden import disruption. The following scenario framework is therefore designed to investigate proactive measures for addressing this risk.

The scenario ***naive planning*** serves as our baseline, where the optimal import structure is determined solely by cost-minimization, excluding any risk mitigation strategies. While such an optimization may lead to highly concentrated import markets and associated disruption risks, it provides an essential benchmark against which the other mitigation strategies are evaluated.

The scenario ***diversification*** investigates trade decisions and their impact on the European energy system under enforced diversification of hydrogen imports. The Herfindahl-Hirschman-Index (HHI) is a widely used metric to measure market concentration and competition. As an example, De Rosa et al. (2022) use the HHI to quantify the historical diversification of energy supply in the European Union, whereas Kim et al. (2025) use an adjusted HHI to analyze the energy security of coal, oil, and natural gas, decomposing risk related to market concentration and geopolitics. In our model, we integrate the HHI as a constraint, thereby enforcing a minimum degree of diversification, represented by an HHI threshold. We test four specifications of this HHI threshold (HHI $\leq$ 4,000, 3,000, 2,000, and 1,000), enabling us to quantify the additional costs associated with varying degrees of diversification. Mathematically, the HHI is defined as the sum of the squared market shares s of each exporter i (cf. Equation 10). For instance, a monopolistic market would have an HHI of 10,000, while a market with five exporters, each holding an equal share, would result in an HHI of 2,000, given that s is expressed in percentage terms.

$$\mathrm{HHI} = \sum_i s_i^2 \tag{10}$$

In our analysis, the application of this metric must be contextualized. While the HHI is a standard measure of market concentration, we employ it as a proxy to manage the criticality of an exporter disruption. As our modeling framework is based on LTCs, neglecting a hypothetical emergence of a spot market, a sudden supply disruption cannot be replaced. Therefore, each exporter is pivotal. Consequently, the HHI in our framework measures the concentration of a non-replaceable disruption risk. For this reason, we apply the HHI to the import market, i.e., the part of the hydrogen supply subject to exogenous risk. Enforcing a low HHI threshold is thus a mechanism to reduce the potential magnitude of damage from any single disruption.

The quadratic nature of the HHI term necessitates reformulating the HYEBRID model as a quadratic-constrained problem, as the market share s is a variable in our model. To maintain computational feasibility, we linearize this constraint, transforming HYEBRID into a mixed-integer linear program. However, even with linearization, s would remain non-linear as both exports from a single exporter and total exports are variables. Therefore, we fix the total quantity of all exports to the quantity determined in the scenario *naive planning* when implementing this constraint, and explore the implications of lower total exports in the *combined* scenario.

In the scenario ***reduction***, we optimize trade decisions and the European energy system configuration, assuming a lower total quantity of imports compared to the scenario *naive planning*. This scenario includes four specifications, with total import volumes set to 75%, 50%, 25%, and 0% of the level determined in the *naive planning* scenario. The rationale behind this scenario is to reduce Europe's exposure to unexpected shortfalls in imports, consequently fostering a more independent European hydrogen supply.

Finally, the scenario ***combined strategies*** evaluates the simultaneous implementation of both import *diversification* and *reduction* measures. This comprehensive scenario framework allows us to systematically assess the effects of each mitigation strategy, individually and in combination, on total system costs, exporter selection and import structures.

4. Results

This section presents the results of the analysis, organized as follows. First, we present the LTC prices derived from the stochastic LCOH calculation for exporting countries. We then detail the results of the scenario *naive planning*, which does not apply a strategy to hedge against the risk of import disruption. Subsequently, we explore the results of the mitigation strategies: *diversification*, *reduction*, and *combined strategies*.

4.1. Hydrogen Import Prices

This section presents the LTC prices derived from the stochastic optimization of LCOH. These LTC prices are key input data for the cost optimization within the HYEBRID model. Figure 6 illustrates LTC prices from various exporting regions to Germany, considering different RES technologies (wind onshore, wind offshore, and solar PV). A comprehensive table detailing LTC prices for a wider range of importing countries is provided in Table E2 in the Appendix.

The results show significant differences in LTC prices across RES technologies and exporting countries. LTCs based on wind onshore (81.3–205.8 EUR/MWh) and PV (88.9–141.8 EUR/MWh) generally exhibit lower prices, while wind offshore (119.2–395.4 EUR/MWh) tends to be more expensive due to higher specific investment costs. Lower LTC prices are typically observed for regions with higher full-load hours (FLH) and renewable energy (RE) yields, as well as shorter transport distances to Europe (e.g., Morocco or Eurasia). The LTC prices presented in Table E2 vary by importing country due to differences in transport distances and available transport options (pipeline-based or seaborne).

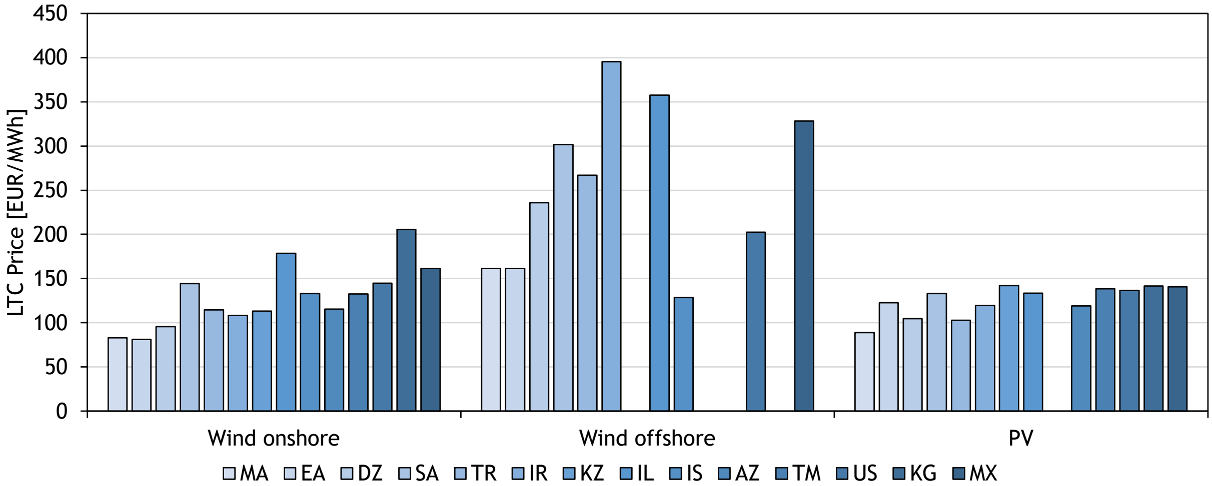

Figure (6) LTC prices including transport to Germany from various exporters. See Table E2 in the Appendix for more importing countries

4.2. Value of stochastic solution

To ensure a reliable and cost-efficient energy system, it is crucial to account for uncertainty in the investment planning stage. A deterministic approach, relying on a single weather year for investment decisions, can lead to a system design that is not robust enough to handle a wide spectrum of weather conditions. This results in lower system reliability when weather characteristics during operation differ from those assumed in the planning stage, potentially causing supply shortfalls (Keutz and Kopp, 2025). A stochastic modeling approach, in contrast, optimizes investments across a range of possible weather scenarios, leading to a more resilient system configuration.

The benefit of this approach is quantified by the Value of the Stochastic Solution (VSS). This metric measures the cost difference between a stochastic model and a deterministic model that uses the expected values of the uncertain parameters (Conejo et al., 2010). For a cost minimization problem, it can be calculated as:

$$VSS = TSC^{Det} - TSC^{Stoch} \tag{11}$$

TSC^{Stoch} represents the total system costs from the stochastic model. TSC^{Det} represents the total system costs obtained after first solving a deterministic problem, using an average weather year to identify investment decisions, and then evaluating the system's performance across all five weather scenarios. For this comparison, all relative costs are expressed as a percentage of the total deterministic system costs TSC^{Det} which serves as the 100% baseline. As shown in Figure 7, the deterministic approach leads to an underinvestment in assets. This results in lower investment and dispatch costs (61.2%). However, the system designed with the deterministic approach is unable to cope with varying weather conditions, resulting in significant costs for uncovered demand (38.8%), assuming a VOLL of 5,000 EUR/MWh. In contrast, the stochastic model leads to higher upfront investment and dispatch costs (64.6%) to build a resilient system that almost entirely avoids reliability penalties, incurring only 0.1% in costs for uncovered demand. The total economic benefit of adopting the robust stochastic approach, the VSS, is 35.3% of deterministic system costs.

While the investment and dispatch costs would adjust slightly to a different VOLL, the costs for uncovered demand would change proportionally, significantly altering the total costs of the deterministic approach.

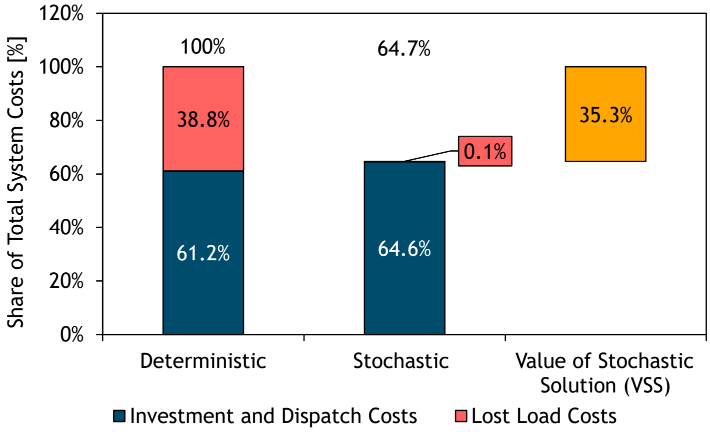

Figure (7) Comparison of total system costs from stochastic and deterministic modeling approaches, assuming a VOLL of 5,000 EUR/MWh

The primary implication of the stochastic approach is a strategic shift towards greater investment in system flexibility, particularly a substantial increase in hydrogen storage capacity (349 TWh vs. 215 TWh) and hydrogen import quantity (916 TWh vs. 685 TWh), to manage weather-induced variability from both domestic production and imports.

4.3. Naive planning

This section presents the results of the scenario *naive planning*, establishing a reference point against which to evaluate the impact of import risk mitigation strategies. The optimization of import decisions in HYEBRID is based on the LTC prices shown in Section 4.1 as well as the weather-dependent delivery profile for each LTC. In addition to import decisions, HYEBRID simultaneously optimizes investment and dispatch decisions in Europe for the target year 2050. As outlined in Section 3.3, the subsequent runs with HYEBRID incorporate five weather years (1992, 1995, 1997, 2010, and 2012), consistent with those used in the LTC price calculation.

Figure 8 illustrates the resulting investment and dispatch[2] decisions for the European electricity and hydrogen sector. The results exhibit a significant deployment of RES, with available wind and PV electricity reaching 6,254 TWh. RES are complemented by battery and H2-to-power capacity, guaranteeing a secure operation of the power system. More than two-thirds of the European hydrogen demand is served by domestic production (1,971 TWh), provided by a total of 665 GW of electrolysis capacity in Europe. To balance intermittent hydrogen production, imports, and demand, 349 TWh of hydrogen storage capacity is employed. The corresponding injection capacity for hydrogen storage is 4,607 GWh/d, while the withdrawal capacity is 9,141 GWh/d, reflecting the need for rapid withdrawal to meet demand spikes from the electricity sector.

[2]All dispatch results shown are weighted averages from five weather years, with each year's probability of occurrence accounted for, as detailed in Section 3.

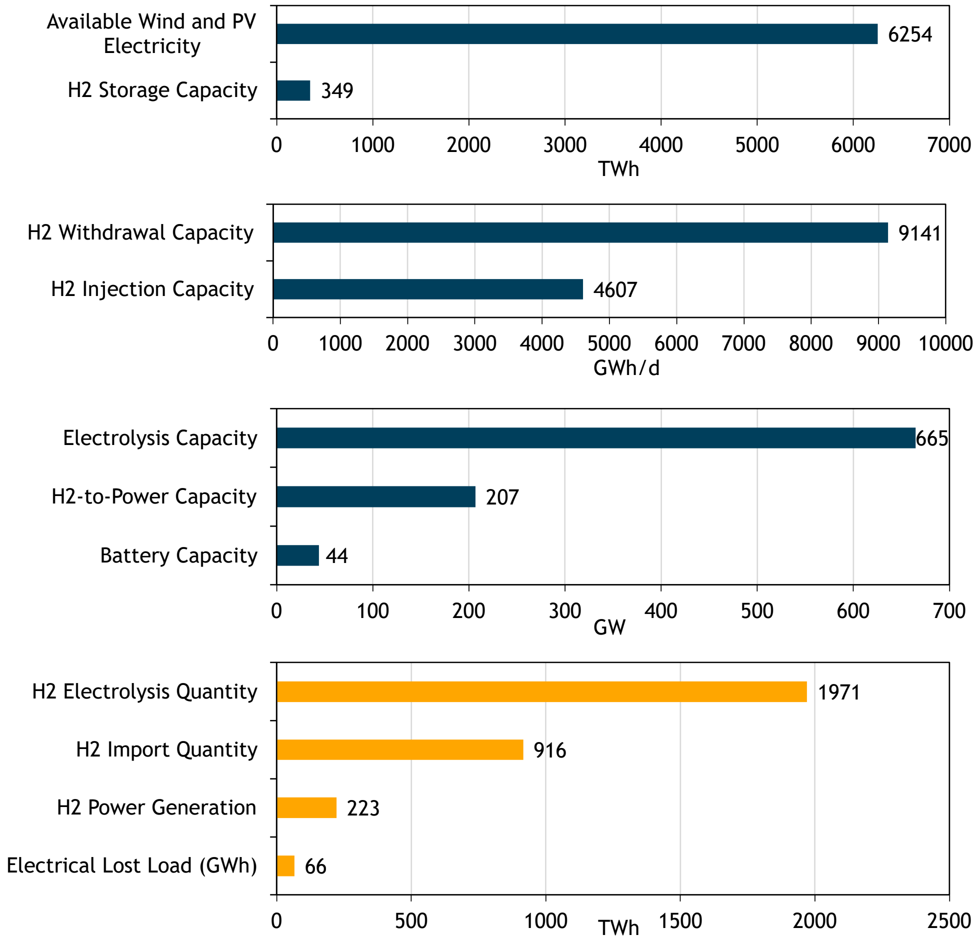

Figure (8) Overview of investment (blue) and dispatch (yellow) results for the scenario *naive planning* in HYEBRID

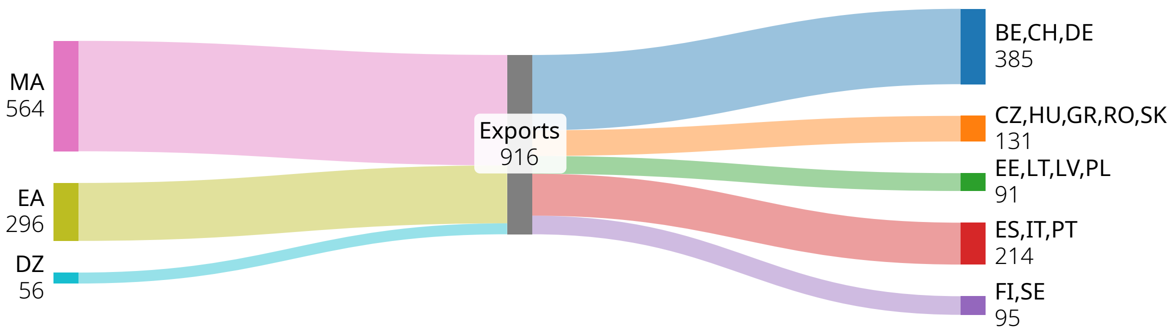

Figure (9) Average annual hydrogen trade flows in the scenario *naive planning*

The total hydrogen import quantity amounts to 916 TWh, covering roughly one-third of the European hydrogen demand in 2050. These imports are sourced from three major exporters—Morocco, Eurasia, and Algeria—all supplying hydrogen exclusively via pipeline. This import structure yields a Herfindahl-Hirschman Index (HHI) of 4,800, indicating a concentrated market. As detailed in Section 3.5, this high HHI indicates a significant security risk, as the system is exposed to a disruption of pivotal exporters. The optimization in HYEBRID takes into account both the price and temporal structure of deliveries associated with an LTC. Our results show that the model selects exporters based on the lowest prices; therefore, variations in the delivery profile between exporters do not significantly influence import decisions in the scenario *naive planning*. This contrasts with the subsequent scenarios, where weather variability becomes a more decisive factor for import decisions.

4.4. Mitigation of Hydrogen Import Risk by Diversification of Imports

The first risk mitigation strategy, *diversification*, forces the model to select a broader range of import sources by imposing increasingly strict HHI targets. To isolate the effect of *diversification* through HHI targets, the total import quantity is kept constant at 916 TWh, matching the level from the scenario *naive planning*.

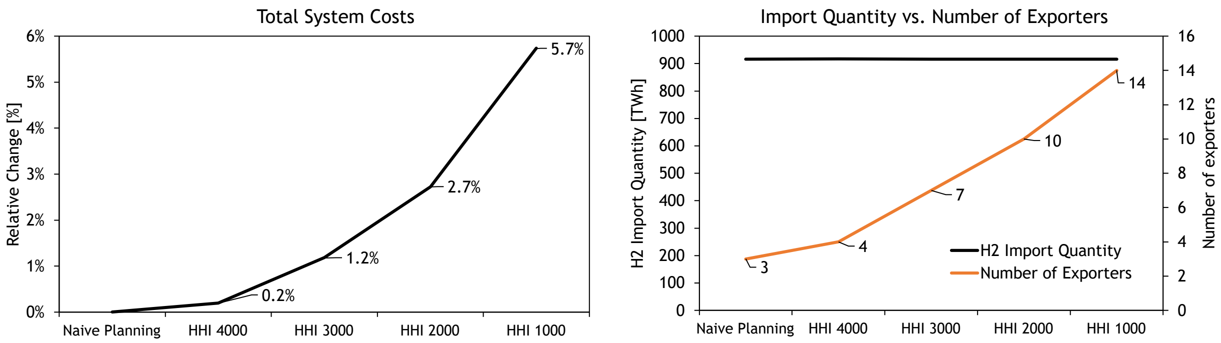

Figure (10) Impact of *diversification* of H2 imports by HHI targets on total system costs and number of exporters

Figure 10 depicts the effects of stricter HHI targets on total system costs and import structures. The number of exporters increases from three in the scenario *naive planning* to fourteen in the HHI 1,000 specification. As a result, the import share of individual exporters decreases significantly: Morocco, the largest exporter in the scenario *naive planning*, drops from 20% to 6% market share under the HHI 1,000 target. However, diversification comes at a cost. The stricter the HHI target, the higher the total system costs, as shown in Figure 10. In the scenario *naive planning*, exporters with high full-load hours (FLH), large RE potentials, and in proximity to Europe are preferred. As the HHI target tightens, exporters with lower FLH and RE potentials, and often greater distances from Europe are contracted, requiring more expensive transport options, such as seaborne imports. Consequently, average LTC prices increase, resulting in additional system costs. The shape of the resulting system cost curve is convex as a function of the HHI, indicating that marginal system costs increase as diversification is strengthened. The maximum system costs are found in the specification HHI 1,000, with a cost mark-up of 5.7% compared to the scenario *naive planning*. Despite these higher costs, the overall asset configuration of electricity and hydrogen infrastructure is only marginally affected. The cost increase is primarily driven by more expensive hydrogen import procurement.

To understand the dynamics of increased procurement costs, Figure 11 illustrates a detailed overview of the LTC prices and corresponding export volumes for each exporter, presented in ascending order of price. The LTC prices shown represent a European-wide volume-weighted average import price for hydrogen, reflecting individual deliveries and transport costs to various European countries. The basis for these weighted import prices is detailed in Section 4.1 (cf. Figure 6 and Table E2 in the Appendix). This figure highlights the relationship between import prices and export volumes at different stages of diversification. As the HHI target becomes stricter, more exporters are selected by the model, leading to greater diversification of the import structures. In the HHI 2,000 and HHI 1,000 specifications, several exporters with relatively high prices are selected with similar export volumes, resulting in similar individual contributions to the overall HHI. Simultaneously, individual export volumes decrease as the model distributes the import volume more evenly across a larger number of exporters.

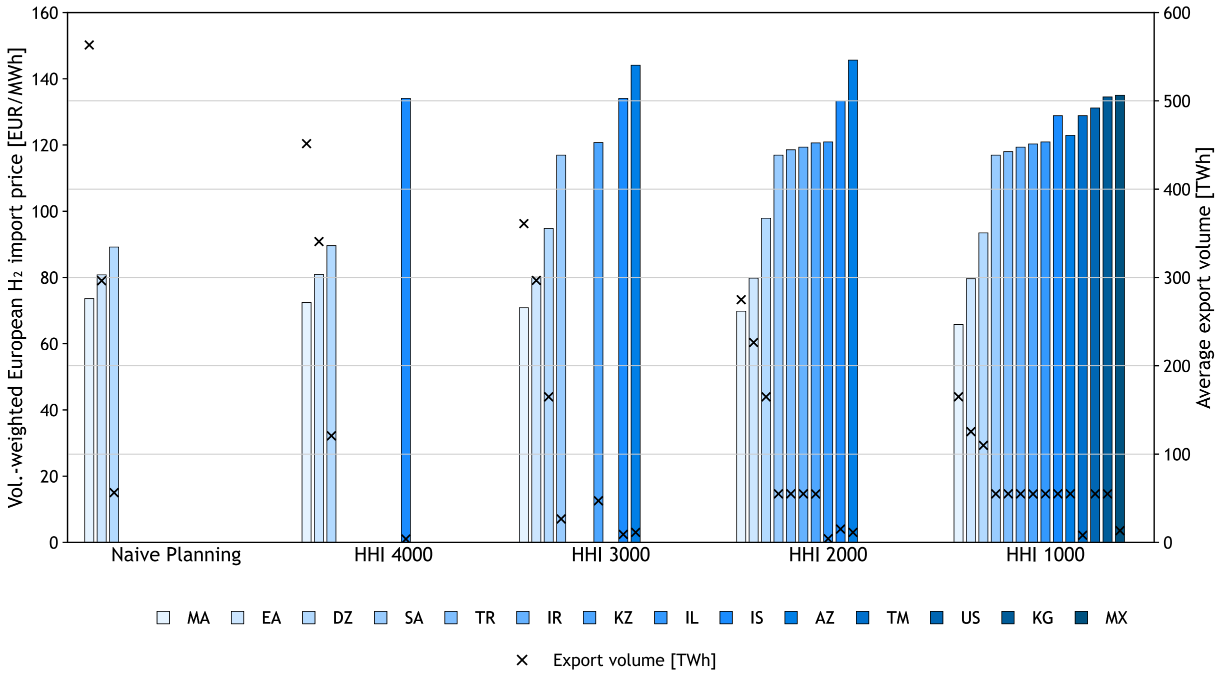

Figure (11) Volume-weighted European hydrogen import prices (EUR/MWh) by exporter and HHI-target

Interestingly, the results reveal that LCOH is not the sole decisive factor for import decisions; the system-friendliness of a delivery profile is crucial. For example, in the scenario HHI 4,000, imports from Morocco (MA), Eurasia (EA), and Algeria (DZ) are contracted, similar to the scenario *naive planning*. Due to the HHI target, additional exporters must be included. From a price perspective, the next most cost-efficient exporter would be Saudi Arabia (SA), followed by Turkey (TR), and Iran (IR) (cf. Figure 11).

Yet, instead of prioritizing these low-cost exporters, imports from Iceland (IS) are contracted at a higher cost. The rationale for this decision appears to be the weather-dependent delivery profile of Iceland, which presumably better aligns with the required import profile. Similar import decisions and observations can be found in the HHI 3,000 case. This demonstrates that non-cost factors, such as weather variability and the resulting import profile, play a role in the import decision. However, providing conclusive evidence for the model's exact reasoning is challenging due to its inherent complexity.

4.5. Mitigation of Hydrogen Import Risk by Reduction of Imports

The second risk mitigation strategy, *reduction*, explores the effects of reducing hydrogen imports through import share targets. These targets are implemented as exogenous caps on total European hydrogen imports, based on the import quantity of the scenario *naive planning*. This approach forces the optimization to reduce hydrogen imports from 916 TWh to zero in four equidistant steps, resulting in fixed hydrogen import volumes of 687 TWh, 458 TWh, 229 TWh, and 0 TWh, respectively. In contrast to the strategy of import *diversification* using HHI targets, the strategy of import *reduction* only limits the total import volumes, allowing the model to select the most cost-effective exporters within that cap.

Figure 12 depicts the effects of reduced hydrogen imports on total system costs and import structures. The results indicate that reduced hydrogen imports are substituted by increased domestic hydrogen production within Europe. Consequently, electrolysis production increases proportionally to the reduction in imports. However, this increase is slightly less than the corresponding reduction in imports, as the hydrogen demand from H2-to-power plants is also reduced due to the concurrent build-up of domestic RES capacities. In the extreme case of no imports (scenario Import 0%), a self-sufficient electricity and hydrogen system within Europe is established. Therefore, domestic hydrogen production amounts to 2,847 TWh, a 44% increase compared to the scenario *naive planning*.

The import share targets do not alter the structure of exporters for European hydrogen imports. The model consistently selects the same three exporters as in the scenario *naive planning*: Morocco, Eurasia, and Algeria. Morocco's import share increases substantially from 32% in the scenario *naive planning* to nearly 90% in the scenario Import 50%. This leads to a HHI of 7,900, significantly higher than in the scenario *naive planning*, indicating a very high concentration of the import market.

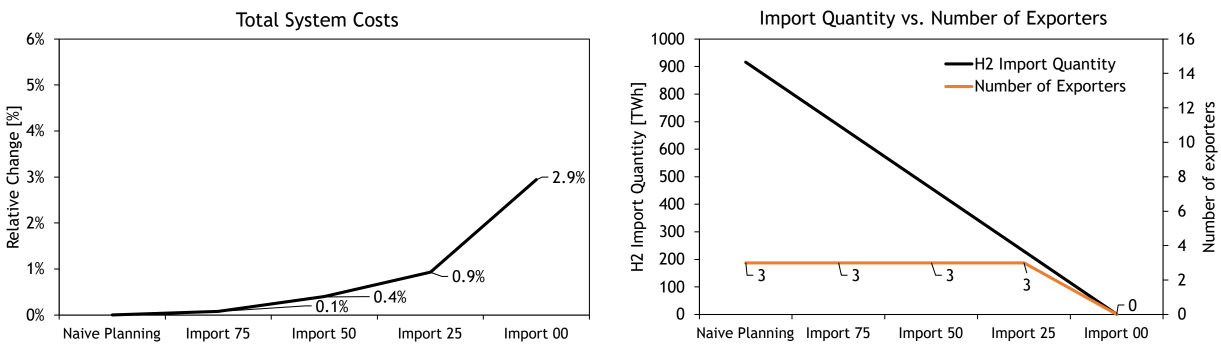

Figure (12) Impact of *reduction* of hydrogen imports by import share targets on total system costs and number of exporters

This shift towards higher levels of self-sufficiency, culminating in a solely self-sufficient European energy system, results in additional system costs. The stricter the import share targets become, the more the total system costs increase (depicted in Figure 12). Again, the cost curve is convex, indicating increasing marginal costs as import quantities are reduced. The maximum increase in total system costs is observed in the specification Import 0%, with a cost mark-up of 2.9% compared to the scenario *naive planning*.

It is important to note that this 2.9% cost mark-up represents a conservative estimate, as it is highly dependent on the assumed cost of capital for domestic versus non-EU production. The WACC spread assumed in these results is 6% ($WACC_{non-EU}$ - $WACC_{EU}$), reflecting higher perceived investment risks for non-EU projects. This spread increases the price of imports and thus narrows the cost gap compared to full autarky (Import 0% specification). Figure 13 illustrates this sensitivity. As the WACC spread decreases, imports become comparatively cheaper, and the additional system costs for full self-sufficiency rise significantly. For instance, assuming equal WACC (0% WACC spread), results in an increase of the cost premium for the scenario *Import 00* of 13.6%.

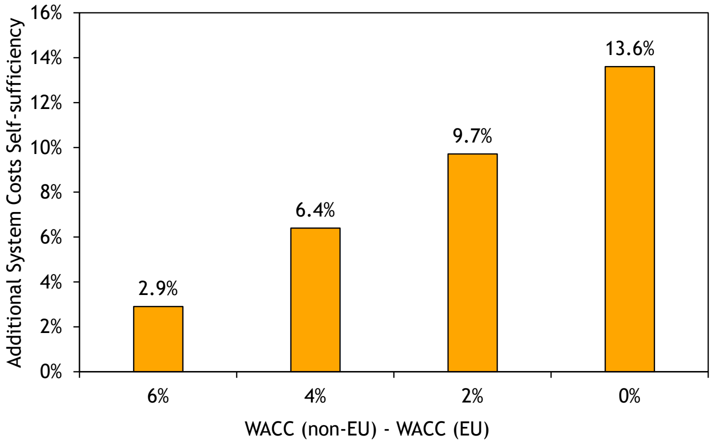

Figure (13) Sensitivity of additional system costs for autarky as a function of the WACC spread between exporters and the EU

In contrast to the strategy *diversification* using HHI targets, where higher system costs are driven by more expensive hydrogen imports, the cost increases in the import *reduction* specifications arise from substantial investments in domestic hydrogen production systems. In the Import 0% specification, the capacity increase compared to the scenario *naive planning* amounts to 39% for electrolysis capacity, 22% for available wind and PV electricity, and 6% for H2 storage capacity.

4.6. Mitigation of Hydrogen Import Risk by Combined Strategies

This section investigates the combined effects of diversifying and reducing hydrogen imports to provide a more comprehensive assessment of import risk mitigation. While the preceding sections analyze each strategy in isolation, their simultaneous implementation reveals interdependent effects on the optimal import strategy and energy system configuration. To manage the analytical complexity of the twelve possible combinations (four HHI targets and three import share targets), we present a focused analysis highlighting key trends and the most salient findings.

We present the results for four representative combined specifications:

- **HHI 4,000 75:** This specification combines a moderate diversification target (HHI 4,000) with a relatively high import share (75%). It represents a scenario where policymakers prioritize low-cost imports while gradually introducing diversification to mitigate disruption risks.

- **HHI 1,000 75:** This specification examines the effect of stringent diversification (HHI 1,000) while maintaining a high import share (75%). It highlights the impact of strong diversification when import reduction is less pronounced.

- **HHI 4,000 25:** This specification explores the impact of a significant *reduction* of imports compared to the scenario *naive planning* (25% import share) while allowing for moderate diversification (HHI 4,000). It shows the system's response when reliance on imports is minimized, but some diversification is still pursued.

- **HHI 1,000 25:** This specification represents the most restrictive case, combining stringent diversification (HHI 1,000) with a substantial reduction in imports (25% import share). It illustrates the potential system-wide costs of pursuing ambitious energy security goals.

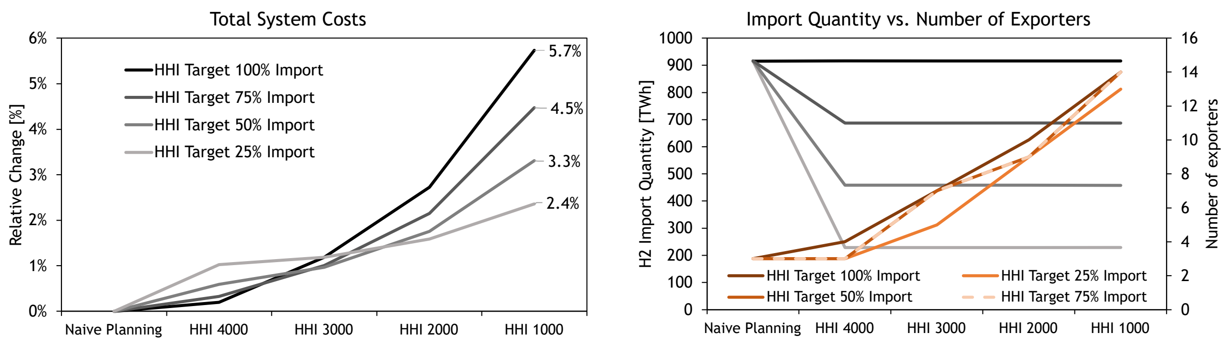

Figure (14) Impact of *combined diversification* and *reduction* of H2 imports on total system costs and number of exporters

The specifications are chosen to provide a balanced overview, capturing the effects of both individual strategies and their combined influence on system costs and import structure. Figure 14 presents the impact of the *combined strategies* on total system costs and the number of exporters.

System Costs: As observed for the individual strategies, stricter HHI targets and lower import shares generally lead to increased system costs. This trend is also evident in the scenario *combined strategies*, with HHI 1,000 25 exhibiting the highest cost increase and HHI 4,000 75 the lowest. However, the cost increase is not simply additive. For instance, combining a 25% import share with HHI 4,000 results in a smaller cost increase than the sum of the individual cost increases for the HHI 4,000 and Import 25% scenarios (cf. Figures 10 and 12). This suggests a partial mitigating effect, where reduced import volumes lessen the cost burden of diversification. Conversely, combining stringent diversification (HHI 1,000) with a high import share (75%) results in a near-additive cost increase, indicating that the cost of strong diversification is more pronounced when import volumes remain high.

Number of Exporters: The number of exporters is primarily driven by the HHI target. Specifications with HHI 1,000 consistently show a larger number of exporters compared to HHI 4,000, regardless of the import share target. The import share target influences the absolute import volumes from these exporters. With a 25% import share, the overall import volume is lower, leading to smaller individual export volumes even with a high number of exporters.

These findings highlight the complex interplay between *diversification* and *reduction*. While both strategies individually increase system costs, their combined effect exhibits non-linear interactions. Reducing import volumes can partially offset the cost of diversification, but stringent diversification remains costly, especially when import volumes are high.

4.7. Relating the cost of autarky to perceived import disruption risk

Autarky results in a cost mark-up of 2.9% compared to the scenario *naive planning*. This premium of 2.9% is equivalent to approximately 12 billion EUR annually. This section contextualizes this cost of security by determining the perceived disruption probability for a single exporter at which the additional costs for autarky become indifferent to the *naive planning*.

We translate the 12 billion EUR additional system costs into a disruption probability for each of the three main exporters identified in the scenario *naive planning*: Morocco, Eurasia, and Algeria. This probability is calculated as the indifference point where the expected annual cost of a potential disruption from a single exporter (probability, disruption volume, and VOLL) equals the cost mark-up of autarky of the scenario *Import 00*. The results are presented in Figure 15.

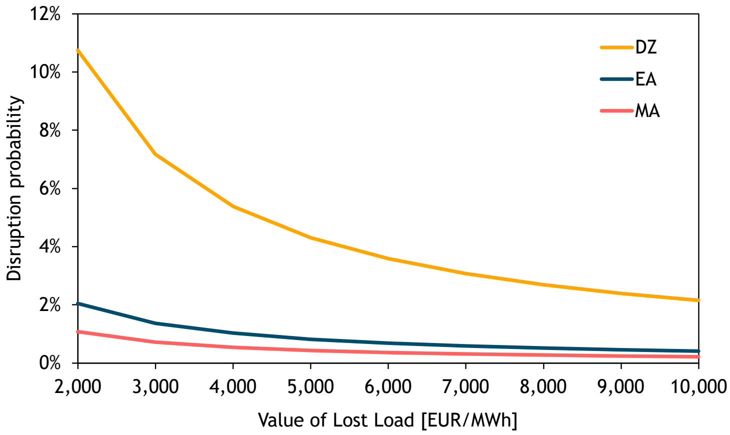

Figure (15) Disruption probability (by exporter) required to justify the cost of full autarky, shown against the Value of Lost Load

The analysis reveals two key insights. First, the calculated disruption probability has an inverse relationship with the VOLL; the higher the assumed economic damage of a disruption, the lower the disruption probability needs to be to justify the cost of autarky. Second, the disruption probability differs significantly based on the import volume of the specific exporter, meaning the costs of autarky can be justified under very different risk perceptions. For example, the autarky cost can be reasonable given a low perceived annual disruption probability for the largest supplier, Morocco (1.1 % at a VOLL of 2,000 EUR/MWh), whereas it requires a significantly higher perceived probability for the smallest supplier, Algeria (10.8% at a VOLL of 2,000 EUR/MWh).

This analysis provides a benchmark for decision-making. By comparing specific geopolitical risk assessments for each hydrogen exporter against the calculated disruption probabilities, an economically informed decision can be made on whether the cost premium for full self-sufficiency is a justifiable investment.

5. Discussion

This section summarizes the key findings of our analysis and highlights real-world policy implications. In addition, it reflects on the methodology, assumptions, and limitations of this work.

5.1. Stochastic calculation of LCOH

This work is the first to stochastically derive LCOH for a set of potential exporting countries worldwide, building upon the methodological framework introduced in Moritz et al. (2023). The stochastic formulation enables the explicit consideration of inter-annual weather variability, and thus, incorporates hydrogen production variability into the decision rationale of exporters. As a result, the asset configuration and LCOH derived are valid over a range of weather years rather than a single deterministic realization. A key insight from our analysis is that accounting for a sufficiently large set of weather data affects the efficiency of the asset configuration in exporting countries and the basis for determining the offtake price for potential LTCs.

5.2. Stochastic optimization of European hydrogen import decisions

We optimize European import decisions, using LTCs with the stochastically determined LCOH as a reference point for LTC prices. A key contribution is that the model HYEBRID, which optimizes European investment decisions, is stochastically expanded to represent the same uncertainty-aware framework as the determination of LCOH.

We quantify the value to the stochastic extension in the form of the Value of Stochastic Solution (VSS). The VSS amounts to a reduction in system costs of 35%, and represents the avoided costs of supply shortfalls that arise if planning were based on a deterministic, average-weather-year approach. This finding highlights the critical need for long-term planning frameworks to account for weather variability already in the investment stage. This need is often overlooked in current planning, such as the TYNDP reports (ENTSOE and ENTSOG, 2022, 2025) or the Long-term Scenarios by Sensfuß et al. (2024), which rely on a deterministic optimization. However, it should be noted that the precise magnitude of the VSS is highly sensitive to the assumed VOLL, which scales the penalty for supply shortfalls.

The stochastic representation of weather in the optimization of European assets points to higher infrastructure requirements. Specifically, the analysis reveals significant balancing challenges that necessitate a substantial expansion of hydrogen storage capacity within Europe. In the scenario *naive planning*, we find that 349 TWh of storage is cost-efficient, substantially higher than in most other studies (Neumann et al. (2023): max. 43 TWh, Moser et al. (2020): 45 TWh, Keutz and Kopp (2025): max. 81 TWh, Frischmuth et al. (2024): max. 221 TWh, Sensfuß et al. (2024): max. 240 TWh, and Schnaars et al. (2024): max. 275 TWh).

The scenario *naive planning* further reveals a mean annual import quantity of 916 TWh, a figure that is sensitive to the underlying cost assumptions from Moritz et al. (2023). This translates to approximately one-third of the total European hydrogen demand. These imports are sourced from the three exporters with the lowest LTC prices: Morocco, Eurasia, and Algeria. An ex-post analysis of the import structure yields an HHI of 4,800, indicating a high level of market concentration. Such a concentrated market could pose a severe risk to Europe's security of supply and affordability in the event of sudden exporter disruptions.

5.3. Investigation of mitigation strategies

To address the vulnerability to an exporter disruption, we investigate two exemplary strategies that mitigate the risk of a sudden disruption: *diversification* and *reduction* of imports. Diversification, enforced by imposing a maximum HHI in the optimization, leads to a more diverse exporter portfolio. For an HHI of 1,000, the number of exporters increases to 14, resulting in an annual system cost increase of 5.7% compared to the scenario *naive planning*. This cost increase is primarily attributed to the need to contract more expensive LTCs. The second mitigation strategy, *reduction* of imports, restricts the total amount of imports, thereby decreasing Europe's dependence on external supply. In the extreme case of European autarky (zero imports), the additional annual system costs amount to 2.9%. Substituting imports with domestic production necessitates significantly more renewable capacity and electrolysis. The additional system costs of full independence in hydrogen supply (+2.9%) are in line with the results of Kountouris et al. (2024b), who find additional system costs of 3% with a similar approach. We note that this quantification is conservative given that we assume significantly higher WACC in exporting countries than in Europe, as pointed out in Section 4.5.

Finally, combining the *diversification* and *reduction* strategies provides a more granular understanding of mitigation options. Our analysis suggests that maintaining the baseline import level (one-third of European demand) while diversifying is generally more costly than reducing overall imports. The finding is highly dependent on the relationship between LTC prices of different exporters; if the supply curve of exporters were steeper, this relationship would become even more pronounced. Therefore, for Europe to manage disruption risk effectively and at moderate additional costs, a precise assessment of these cost relationships is crucial.

Collectively, our findings on these risk mitigation strategies offer crucial strategic insights for European energy security policy and long-term infrastructure planning. As analyzed in Section 4.7, relating the cost of autarky to perceived import disruption risk provides a benchmark for policymakers: the additional costs of autarky can be justified even with a low perceived disruption probability for the largest exporter (e.g., 1.1% for Morocco at 2,000 EUR/MWh VOLL), but require a significantly higher perceived risk for smaller exporters to be beneficial (e.g. 10.8% for Algeria). Current cross-national long-term infrastructure planning, such as the TYNDP (ENTSOE and ENTSOG, 2025), often treats imports from non-European countries as exogenously given, with variations across scenarios that exhibit several shortcomings. Specifically, these approaches fail to account for the temporal variability of imports, which must be managed within Europe. Additionally, they overlook the potential consequences of import disruptions and do not consider the co-optimization of European infrastructure assets alongside decisions on import quantities. As a result, current methodologies are likely to fall short in terms of both security and cost-efficiency. Our work advocates for a comprehensive and robust analysis of the costs and potentials associated with hydrogen imports, taking into account both inter- and intra-annual production variability. Furthermore, it is crucial to incorporate the risk of import disruptions in the selection of exporters and the development of strategies to mitigate exposure to such disruptions. Finally, these considerations should be integrated into the optimization of European energy assets, thereby enhancing the security and cost-effectiveness of long-term planning.

5.4. Limitations

The results of this work should be interpreted in light of several limitations and underlying assumptions. At a general level, it must be noted that we employ a linear stochastic optimization model that minimizes total system costs, which, by virtue of the duality theorem, is equivalent to the risk-neutral profit maximization of investors. This equivalence requires the existence of complete markets, a condition that may not hold in practice. Moreover, quantitative results, such as the magnitude of hydrogen imports or the required storage capacity, depend on the scenario framework adopted, especially the demand level. Therefore, the results should be interpreted as scenario-consistent rather than absolute projections.

In addition, simplifications are made regarding the temporal and weather representation in the HYEBRID model. We cluster a set of 27 historical weather years into five representative years, which approximate but do not fully capture the true inter-annual variability or the temporal correlations between European and exporting regions (cf. Appendix C). Furthermore, we assume that the weather conditions represented in the investment decision correspond to those in the long-run equilibrium, which is an abstraction, as actual weather patterns are subject to climate change and long-term shifts. Nevertheless, even under these simplifying assumptions, the model is able to generate significant effects of inter-annual weather variability, for example with respect to the LCOH and the VSS. The framework also reveals structural relationships, such as the fact that some costly LTCs are preferred due to more favorable weather profiles.

Further assumptions relate to market and system boundaries. Our approach determines LTC prices solely based on stochastic LCOH, whereas in the real world, prices may include security premia and be influenced by asset cost uncertainties and other factors. We also acknowledge that not accounting for heterogeneity of renewable yields within individual European countries could lead to an underestimation of additional system costs through autarky, given the limited land available for renewable energy in Europe. Furthermore, our analysis assumes no risk of severe disruption originating within Europe.

6. Conclusion

This paper presents a comprehensive stochastic modeling approach to analyze the cost-optimal design and operation of a decarbonized European energy system, with a particular focus on the integration of hydrogen imports and the mitigation of associated disruption risks. By extending the HYEBRID model to incorporate inter-annual weather variability and various import risk mitigation strategies, this research provides crucial insights into the complexities of achieving energy security in a climate-neutral future.

Methodologically, this work introduces a stochastic framework for determining the LCOH for non-European exporters, ensuring robust asset configurations and LTC pricing across diverse weather patterns. The LCOH estimates then inform the stochastic HYEBRID model, which simulates the European hydrogen and electricity system's investment and dispatch decisions under weather uncertainty. The stochastic representation of weather yields a significant advantage, quantified by a 35% reduction in total system costs compared to deterministic planning using an average weather year. A pivotal finding from this modeling is the imperative for a substantial increase in European hydrogen storage capacity, considerably exceeding previous estimates, to effectively manage fluctuations in domestic and imported supply.

Addressing a critical research gap, this study explicitly quantifies the economic implications of hydrogen exporter disruption and various mitigation strategies. Our analysis shows that the cost-optimal scenario *naive planning*, with its highly concentrated import market (HHI 4,800), poses significant supply risks. *Diversification* via stricter HHI targets reduces concentration but incurs higher LTC procurement costs. Conversely, reducing import volumes by increasing domestic production also raises system costs, shifting the burden to domestic infrastructure. The non-linear interplay suggests a balanced approach that can partially offset diversification costs.

This study yields key policy implications for Europe's energy security. Long-term planning should robustly analyze hydrogen import costs and potentials, incorporating production variability. Policymakers should integrate supply disruption risks into exporter selection and the development of mitigation strategies (*diversification* and *reduction* of imports) to enhance security and cost-effectiveness. The relationship between the additional costs of autarky and the perceived disruption probabilities of exporters provides a first quantitative benchmark for this trade-off, demonstrating that the cost premium for full self-sufficiency can be justified by varying levels of perceived disruption risk, depending on an exporter's market share. These insights are vital for informing infrastructure investment and shaping future contractual frameworks to promote long-term supply security.

Despite its significant contributions, this research should be interpreted in light of several limitations. Key modeling assumptions include the existence of complete markets for the stochastic optimization, a simplified weather representation using clustering, and the determination of LTC prices based solely on stochastic LCOH, omitting real-world factors like security premia. The limitations point to valuable directions for future research. Future work could enhance the robustness of our analysis by integrating disruption risk directly into the investment stage of the stochastic optimization and by conducting broader sensitivity analyses on the LCOH calculations. Additionally, investigating alternative LTC designs and the impact of dispatch-stage weather variability that deviates from investment-stage assumptions would provide further valuable insights.

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Appendices

A. Weather data in calculation of LCOH

The calculation of stochastic LCOH requires hourly capacity factors of renewable energy classes for each weather year under consideration. The meteorological data used in Moritz et al. (2023) is based on hourly capacity factors from Pfenninger and Staffell (2016) which are scaled to annual capacity factors stemming from Pietzcker et al. (2014). The inclusion of Pietzcker et al. (2014) allows us to disaggregate renewable technologies into resource classes with different qualities and technical potentials restricting the output of hydrogen production. However, renewable energy potentials and capacity factors from Pietzcker et al. (2014) do not exhibit an hourly profile. Therefore, Brändle et al. (2021) conducts an exponential scaling to generate synthetic hourly profiles matching the capacity factors and potentials outlined in Pietzcker et al. (2014).

To incorporate multiple weather years in our analysis, we adjust the approach in the following way. First, we calculate the annual capacity factor *cfa* of individual weather years per node n and res tech r based on the time series from Pfenninger and Staffell (2016).

$$cfa_{n,s}^{res} = \sum_{h} cf_{n,h,s}^{res} \tag{.1}$$

Second, we determine the relative deviation *delta* of capacity factors per weather year to the mean annual capacity factor *cfma*.

$$delta_{n,s}^{res} = \frac{cfa_{n,s}^{res}}{cfma_{n}^{res}} \tag{.2}$$

Then we define an annual target capacity factor for each year as the *cfo* multiplied by the relative deviation of individual years to the mean.

$$cft_{n,r,s}^{res} = cfo_{n,r}^{res} \cdot delta_{n,s}^{res} \tag{.3}$$

Lastly, we define a final capacity factor *cff*, which reflects the targeted annual capacity factor while keeping the temporal structure of the initial hourly time series. This is done by using an exponential scaling factor σ for each combination of node, resource class, res class and scenario s, similar to the approach used in Brändle et al. (2021).

$$\frac{\sum_{h=1}^{8760} cff_{n,h,r,s}^{res}}{8760} = cft_{n,r,s}^{res} \tag{.4}$$

$$(cf_{n,r,h}^{res})^{\sigma_{n,r,s}^{res}} = cff_{n,h,r,s}^{res} \tag{.5}$$

The values for the exponential scaling factor σ are derived using a non-linear optimization model, minimizing deviations of the scaled original profile to the targeted capacity factor. The objective function and constraint are described in Equation .6 and .7

$$min\ OBJ = slack_{up} + slack_{down} \tag{.6}$$

s.t.

$$cft^{res}_{n,r,s} = \frac{\sum_{h=1}^{8760}(cf^{res}_{n,r,h})^{\sigma^{res}_{n,r,s}}}{8760} + slack_{up} - slack_{down} \tag{.7}$$

This adjusted approach allows us to keep the information on the original intra- and inter-annual weather variability from Pfenninger and Staffell (2016) as well as the relation between capacity factors for each resource class from Pietzcker et al. (2014).

B. Calculating stochastic LCOH

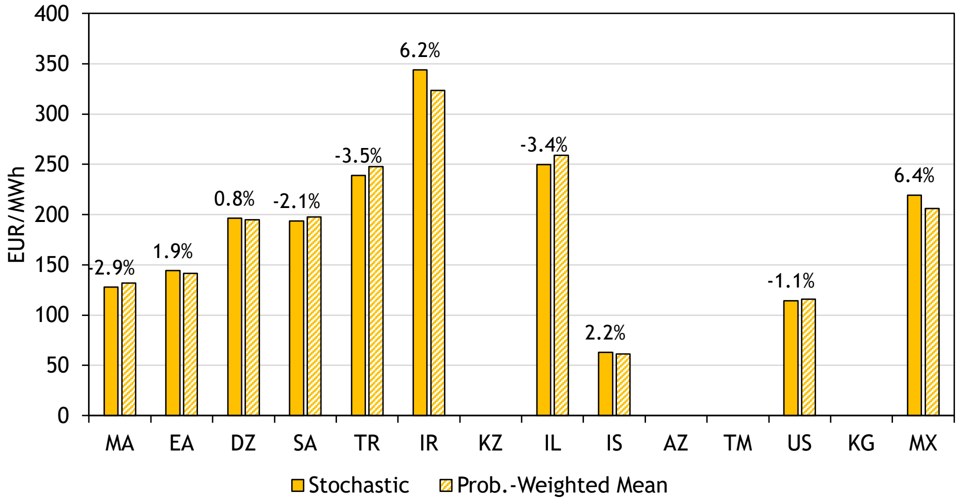

Figure (B1) Comparison of stochastic LCOH and probability-weighted mean LCOH for wind offshore across various exporting countries. Percentages indicate the differences between both methodological approaches.

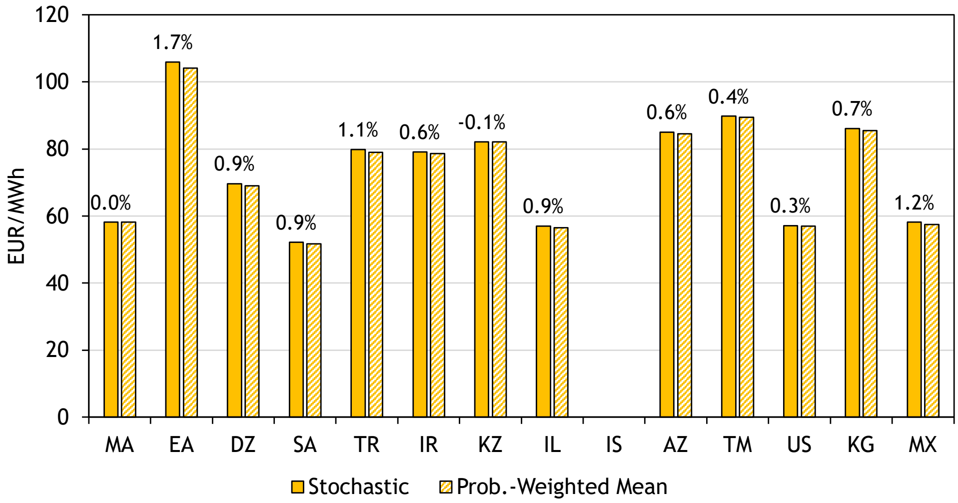

Figure (B2) Comparison of stochastic LCOH and probability-weighted mean LCOH for PV across various exporting countries. Percentages indicate the differences between both methodological approaches.

C. Wind correlation before and after clustering of weather years

Figure C3 shows the correlation of wind onshore[3] capacity factors between the EU (mean) and each exporter for the full dataset of 27 weather years (*before Clustering*) and for the five clustered weather years (*after Clustering*). Although the clustering methodology does not explicitly include correlation as a criterion, both the magnitude and the direction of the correlations are largely preserved, indicating that the clustering adequately retains the interregional dependence structure.

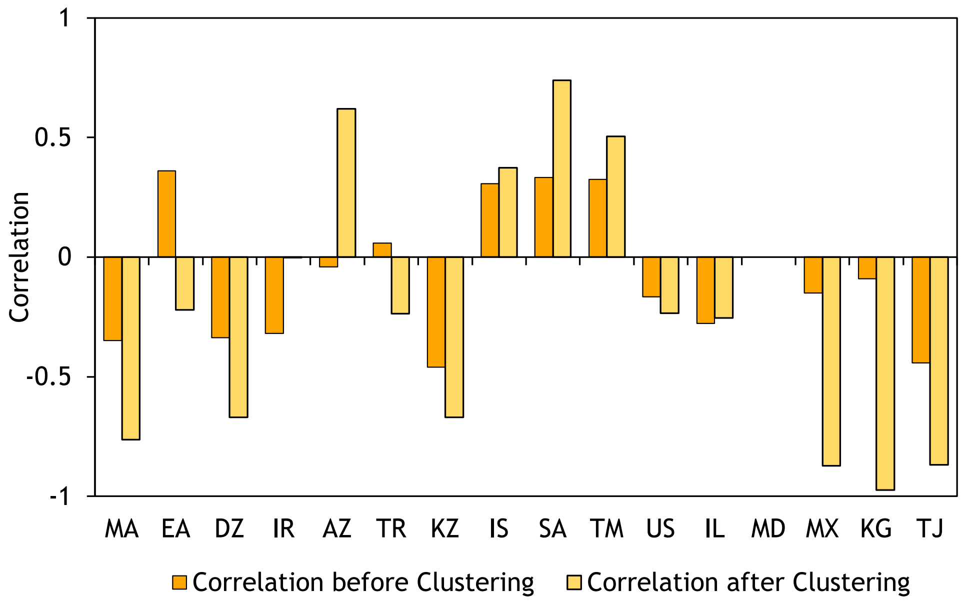

Figure (C3) Correlation of wind onshore capacity factors between EU and exporters.

D. Assumptions and inputs for energy system modeling

Table (D1) Techno-economic assumptions as inputs for energy system model

Technology	Parameter	Unit	Value	Reference
H2 storage capacity	CAPEX - New	tEUR/GWh	350	[1,2]
	CAPEX - Retrofit	tEUR/GWh	300	[1,2]
	OPEX	tEUR/GWh	6.03	[1,2,3,4,5]
	FOM	% of CAPEX/a	4	[1,5]
	Conversion factor H2/CH4	%	20	[6,7]
	Round-trip efficiency	%	90	[8]
	Lifetime	a	33	[9]

[3] We abstract from an evaluation of PV capacity factors, as hydrogen exports based on PV generation play only a subordinate role in our model.

Table (D1) Techno-economic assumptions as inputs for energy system model

Technology	Parameter	Unit	Value	Reference
H2 storage injection & withdrawal capacity	CAPEX - New	tEUR/GWh/d	6,126	[1,10]
H2 pipeline	Conversion factor H2/CH4	%	75	[11]
	Losses	%	1	
Electrolysis	CAPEX	tEUR/GW	392,243	[12]
	FOM	tEUR/GW	10,000	[13]
	Efficiency	%	74	
	Lifetime	a	25	
Battery	CAPEX	tEUR/GW	384,626	[12]
	FOM	tEUR/GW	13,100	[13]
	Efficiency	%	90	
	Lifetime	a	10	
Wind onshore	CAPEX	tEUR/GW	1,117,000	[13]
	FOM	tEUR/GW	13,140	[13]
	Efficiency	%	100	
	Lifetime	a	25	
Wind offshore	CAPEX	tEUR/GW	2,036,000	[13]
	FOM	tEUR/GW	26,280	[13]
	Efficiency	%	100	
	Lifetime	a	25	
Photovoltaics	CAPEX	tEUR/GW	500,000	Assumption
	FOM	tEUR/GW	9,330	[13]
	Efficiency	%	100	
	Lifetime	a	25	
H2-to-power CCGT	CAPEX	tEUR/GW	762,000	[13]
	FOM	tEUR/GW	26,000	[13]
	Efficiency	%	60	
	Lifetime	a	30	
H2-to-power OCGT	CAPEX	tEUR/GW	412,000	[13]
	FOM	tEUR/GW	7,400	[13]
	Efficiency	%	40	

Table (D1) Techno-economic assumptions as inputs for energy system model

Technology	Parameter	Unit	Value	Reference
	Lifetime	a	30	

Table references:[1] van Gessel and Hajibeygi (2023), [2] Frischmuth et al. (2022) , [3] DEA (2022), [4] Yousefi et al. (2023), [5] Noack et al. (2015), [6] Bültemeier et al. (2022), [7], NWR (2021), [8] Tsiklios et al. (2023), [9] Schlund (2023), [10] Schnaars et al. (2024), [11] Galyas et al. (2023), [12] IEA (2023), [13] ENTSOE and ENTSOG (2022)

E. Further results

Table (E2) LCOH including transport costs (EUR/MWh) to selected European countries from various exporters

Importing Country	**Tech.**	MA	RU	DZ	SA	TR	IR	KZ	IL	IS	AZ	TM	US	KG	MX
DE	Wind onshore	83.2	81.3	95.8	144.5	114.7	108.1	113.1	178.6	133.0	115.4	132.5	144.7	205.8	161.5
	Wind offshore	161.3	161.7	236.0	301.6	266.7	395.4	–	357.7	128.7	–	–	202.7	–	328.4
	PV	88.9	122.6	104.5	132.9	103.0	119.4	141.9	133.7	–	119.2	138.5	136.7	141.8	140.8
NL	Wind onshore	76.5	88.0	93.3	138.8	125.0	115.0	119.2	172.4	130.0	122.8	137.7	140.4	213.1	156.8
	Wind offshore	154.0	169.0	233.1	294.0	278.8	404.3	–	349.3	125.7	–	–	197.9	–	322.4
	PV	82.1	129.7	102.0	127.4	113.2	126.3	148.2	128.1	–	126.7	143.8	132.5	148.6	136.4
GB	Wind onshore	83.2	107.7	97.4	137.4	126.9	127.0	121.8	171.0	129.2	127.7	147.3	139.0	217.5	155.5
	Wind offshore	161.1	189.5	237.5	292.3	280.8	419.1	–	347.5	124.9	–	–	196.5	–	320.8
	PV	88.9	149.8	106.1	126.0	115.0	138.4	150.8	126.8	–	131.6	153.5	131.2	152.8	135.0
IT	Wind onshore	85.1	94.8	85.5	127.9	112.4	110.7	117.7	160.4	139.5	117.2	139.8	144.8	209.8	160.2
	Wind offshore	163.5	176.4	224.4	278.0	263.8	398.4	–	331.1	135.1	–	–	202.9	–	326.8
	PV	90.9	136.8	94.1	116.9	100.7	122.0	146.6	117.6	–	121.0	145.9	136.8	145.5	139.5
ES	Wind onshore	60.0	101.7	74.0	134.3	128.6	130.6	132.1	167.2	140.8	134.2	163.6	146.0	233.5	161.4
	Wind offshore	135.9	183.9	211.0	286.2	283.2	424.7	–	340.1	136.3	–	–	204.0	–	327.6
	PV	65.6	144.0	82.5	123.2	116.7	142.2	161.4	123.9	–	138.1	169.8	138.1	167.8	140.8
PL	Wind onshore	86.1	79.4	101.1	145.6	115.6	114.1	108.0	179.8	134.1	120.9	128.9	145.7	198.1	162.6
	Wind offshore	164.5	159.6	242.5	303.3	267.9	403.2	–	359.7	129.7	–	–	204.0	–	330.1
	PV	91.8	120.6	110.0	134.0	103.9	125.5	136.6	134.7	–	124.8	134.9	137.8	134.5	141.9