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Integrated Assessment of Endogenous and Exogenous Uncertainties in Long-Term Energy System Planning

Luca Bianchi[1*], Marco Rossi[1], Giulia Romano[2], Paolo Greco[3]

Abstract

Both internal and external uncertainties heavily impact energy planning processes. In the present study, we introduce a systematic framework to explore the uncertainty domain by integrating mixed-integer linear programming (MILP), Monte Carlo simulations, and machine learning to measure how these uncertainties affect a national energy system at both global and local levels. This methodology facilitates detailed correlation analyses that reveal potential risks and synergies throughout the energy transition, serving as a practical tool for guiding policy decisions. An application to the Swiss energy system demonstrates that while energy independence and carbon neutrality (including negative emissions) are attainable by 2050, the structural configuration of the system fluctuates considerably when subjected to uncertainties. Conditional distribution assessments indicate that carbon capture and storage (CCS), photovoltaics (PV), and wood gasification exhibit the strongest correlations with effective decarbonization. By evaluating the complete uncertainty space and incorporating heterogeneous variables, this research offers enhanced reliability over traditional sensitivity analyses that rely on isolated scenario comparisons. Furthermore, the integration of artificial intelligence (AI) with energy modeling holds substantial promise for broader applications within energy planning, especially regarding novel technologies that face significant developmental uncertainties.

Keywords Uncertainty, Machine learning, Energy planning, Monte Carlo simulation, Correlation analysis

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Introduction

The recent conflict involving Russia and Ukraine has heightened global anxieties regarding energy supply security [1-3]. This occurs alongside international climate objectives established in Paris (Conference of the Parties (COP) 21, 2015) and Sharm El Sheikh (COP 27, 2022), which aim to restrict the increase in global temperatures to under 1.5–2 °C relative to pre-industrial baselines [4]. To achieve these climate goals and strengthen energy independence, energy planning models function as vital decision-making instruments [5-8]. Based on their temporal resolution, these models generally fall into two categories: (1) short-term models operating on scales ranging from (milli)seconds to hours, which are typically applied to examine dynamic system behaviors like the voltage and frequency stability of electrical grids, as seen in Refs. [9-15]; and (2) long-term models, such as those presented in Refs. [16-19], which are instrumental in defining the roles of various technologies—particularly renewable sources—during the energy transition, while also addressing strategic questions regarding the deployment and operation of these assets across hourly, monthly, and annual timeframes.

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Currently, executing systematic uncertainty analyses within long-term energy planning remains challenging owing to two primary obstacles: (1) the high computational demands required for energy models to produce an adequate number of analytical samples; and (2) the absence of structured methodologies to interpret the outcomes of these uncertainties thoroughly. The first issue arises because these optimization problems are inherently complex, involving numerous variables and parameters that can require hours or even days to compute a single scenario, or because the connection between the problem and its overarching structure lacks efficiency. For example, the substantial computational burden of the prominent Markal TIMES energy planning model has been extensively documented in Refs. [20-22]. Regarding the second challenge, contemporary research predominantly addresses uncertain outcomes through scenario analysis, modifying a restricted set of parameters to observe resultant variations. Consequently, the validity of conclusions drawn from this method depends heavily on researchers' subjective expertise, given the limited number of simulations and the potential neglect of impacts from untested variables. As an alternative, Moret *et al.* [23] introduced a robust optimization technique to manage energy uncertainties from a macro perspective; however, its direct application in policy formulation is difficult because the robust variables utilized lack direct physical equivalents. More recently, advancements in machine learning have provided new avenues for investigating the fundamental attributes of complex, multi-variable problems. As highlighted in Ref. [24], machine learning techniques are now widely used to predict, design, and model energy systems —particularly for forecasting consumption, production, and demand—owing to their speed, effectiveness, and precision [25, 26]. Nevertheless, there is a notable scarcity of studies systematically integrating machine learning into long-term energy system modeling and the associated uncertainty evaluations, even though these algorithms are frequently utilized for short-term production and demand forecasting [27-29], as well as day-ahead electricity price predictions [30-33].

In the current paper, we introduce a streamlined methodology for conducting uncertainty assessments by merging Monte Carlo simulations with machine learning techniques. The primary goals are to (a) reveal the conditional distributions and correlations among various energy technologies, and (b) measure their respective impacts on carbon mitigation. The remainder of this manuscript is structured as follows: Chapter (2) outlines the modeling framework, detailing the Energyscope model , and discussing the implementation of the uncertainty analysis. Chapter (3) presents the results of the uncertainty evaluation from a macro-level energy system viewpoint, whereas Chapter (4) focuses on the sector-specific effects of these uncertainties on the energy system. Lastly, Chapter (5) synthesizes the primary contributions of the research and suggests avenues for subsequent investigation.

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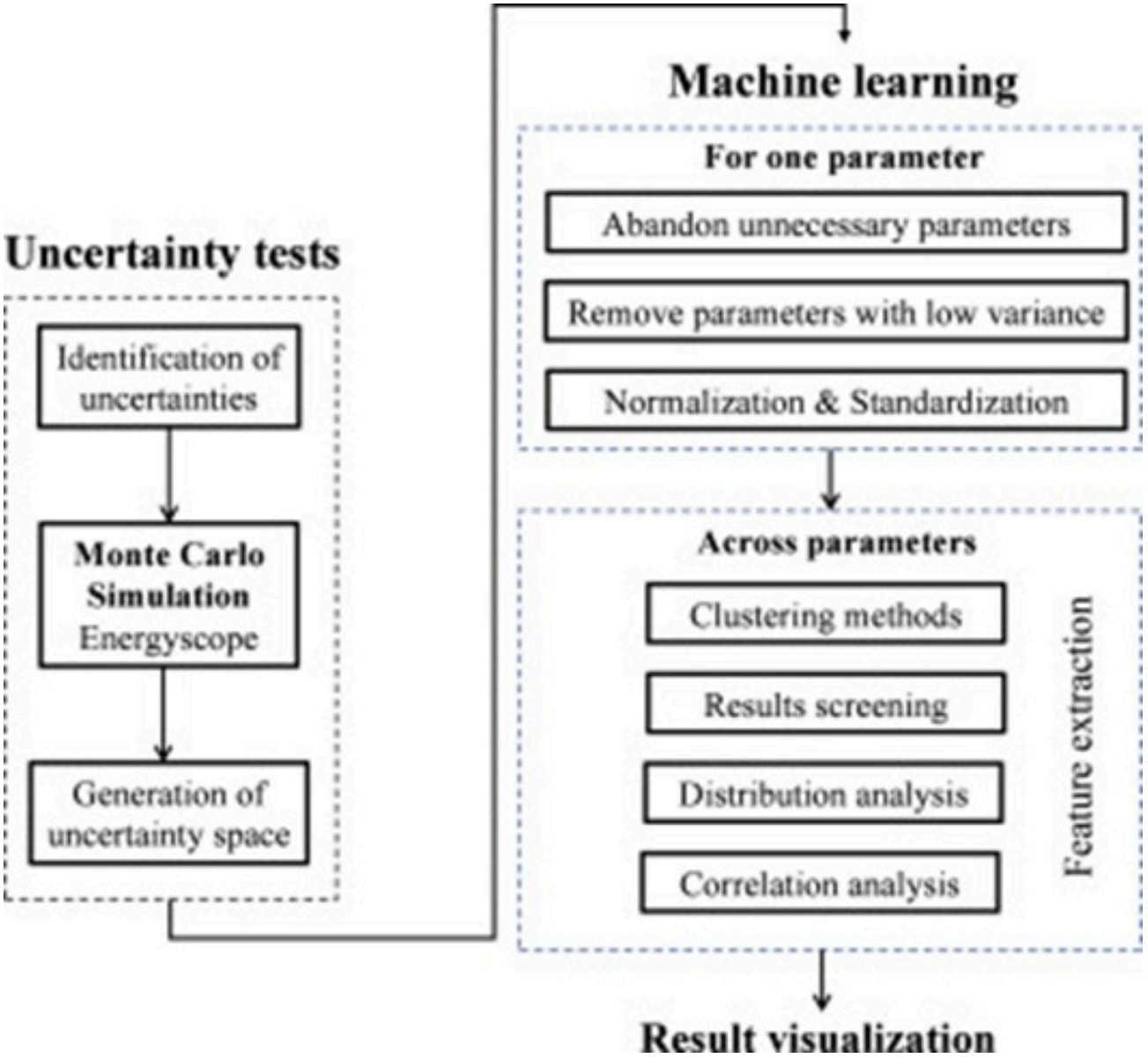


Figure 1. Modeling methodology — uncertainty tests based upon ES and application of machine learning methods.

Materials and Methods

Figure 1 illustrates the methodological framework of this research, which comprises two primary components: (a) Monte Carlo simulations executed via the Energyscope model; and (b) machine learning.

Energyscope model

To simulate the energy system, Energyscope (ES) was utilized to support long-term planning through techno-economic-ecological optimization within a defined geographic boundary. This bottom-up framework functions as a comprehensive representation of the energy system, encompassing over 100 energy conversion technologies designed to fulfill diverse energy demands, including electricity, process heat, space heating (SH), hot water (HW), as well as both freight and passenger transport (encompassing private and public mobility). The original version of Energyscope is available online [34], and it has received continuous updates since 2014. It has been implemented in studies for Switzerland [23, 35-38], Belgium [39], and France alongside Germany [40], with current applications underway for Canada and Western Europe.

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Related research domains include energy storage, mobility optimization, cost analysis, and grid integration. More recently, it has informed energy policy formulation for the Canton of Vaud in Switzerland.

In contrast to many existing energy models that are frequently proprietary and computationally demanding, Energyscope optimizes the operational and investment strategies of a complete energy system by generating a “snapshot” of a specified future year [35, 37]. For this research, the year 2050 is selected as the target time horizon, utilizing a monthly resolution. Beyond offering computational efficiency during uncertainty assessments, monthly models are standard in long-term planning to mitigate the heightened randomness associated with using hourly data to forecast long-term trends [41]. Energyscope operates as an MILP model constructed in AMPL (A Mathematical Programming Language [42]), employing CPLEX [43] as its solver. Throughout this text, decision variables are denoted in bold. The objective function is formulated to minimize the total annual cost (Ctot), which is calculated as the sum of annualized capital expenditures (CAPEX, Cinv), annual variable operational expenditures (OPEX, Cop) associated with resource procurement, and annual fixed OPEX, specifically the maintenance cost (Cmaint), as presented in **Eq. 1.**

$$\min \mathbf{C_{tot}} = \min \Big(\sum_{j \in \mathcal{E}} \frac{i_r (1+i_r)^{n(j)}}{(1+i_r)^{n(j)} - 1} \mathbf{C_{inv}}(j) + \sum_{j \in \mathcal{E}} \mathbf{C_{maint}}(j) + \sum_{r \in R} \sum_{t \in T} \mathbf{C_{op}}(r,t) t_{op}(t) \Big) \quad (1)$$

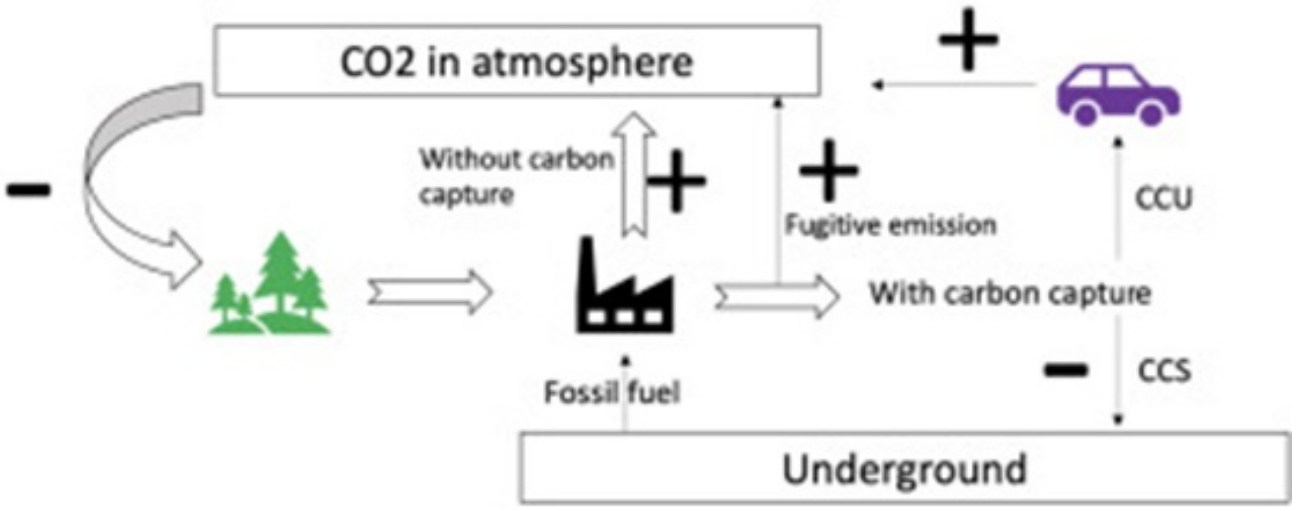


Figure 2. Carbon flow modeling in Energyscope. Positive symbols imply emissions to the atmosphere, while negative symbols denote negative emissions.

where the sets $\mathcal{E}$, $\mathcal{R}$, and T denote the technologies, the resources (including renewables, non-renewables, and imported electricity), and the time periods, respectively. top (t) indicates the duration of month t. The investment cost Cinv (j) is annualized using a factor τ (ir, n (j)), which is defined as a function of the interest rate ir and the anticipated lifetime n (j) for technology j. The efficiency of energy technologies is represented by the transitional matrix η.

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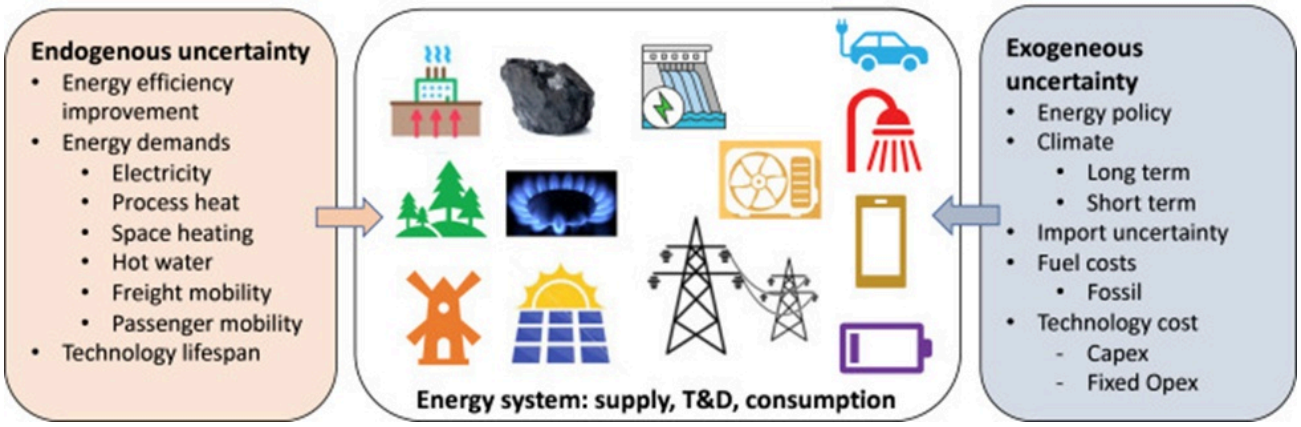


Figure 3. Model scope and uncertainty categories considered in this study.

Beyond traditional evaluations of the energy sector, particular emphasis is placed on carbon flows, reflecting the growing support for carbon capture, utilization, and sequestration (CCUS), with a specific focus on biogenic carbon capture (BECC). **Figure 2** demonstrates the interplay among various carbon sinks and sources across the energy system, the atmosphere, and subterranean storage. To determine aggregate carbon emissions, all positive emissions j+ and negative emissions j- across every technology are aggregated, governed by the ϵ-constraint in **Eq. 3**. In this context, an ϵ value that is positive, zero, or negative corresponds to positive, net-zero, or negative emissions, respectively.

$$\sum_{j^+} E(j^+) + \sum_{j^-} E(j^-) \leq \epsilon \quad (2)$$

Alongside the previously mentioned constraints, additional techno-economic restrictions—such as resource availability, upper and lower bounds on the installed capacity of energy technologies, power grid capacity limits, intermediate conversion, and storage continuity—were established in our prior work [37]. The current research centers on conducting an uncertainty analysis utilizing the Energyscope model.

Monte Carlo simulation

Monte Carlo simulation [44] is a prevalent technique for conducting uncertainty analyses. The initial phase involves pinpointing the sources of uncertainty. For instance, the interest rate is dictated by broader macroeconomic conditions. It is therefore classified as exogenous within this research, whereas the operational lifetime of energy technologies is considered an endogenous uncertainty intrinsic to the energy system. **Figure 3** depicts the scope of the model alongside primary uncertainty sources, which include sector-specific energy demands, investment costs, maintenance expenses, technological lifetimes and potentials, resource availability, and the operational expenditures associated with purchasing fuels and power. Additional variables, including the interest rate, the proportion of district heating, and the adoption rate of electric vehicles, are incorporated, culminating in a total of 441 uncertain parameters.

Subsequently, we run 105 Monte Carlo simulations that update the uncertain parameters within Energyscope, employing a uniform distribution constrained by the established minimum and maximum thresholds. For every test, 125 outcomes are logged, detailing the annual technological outputs, emission levels, and total system cost. Each run requires merely seconds to complete using an Intel(R) Core(TM) i7-8559U CPU @ 2.70 GHz processor. A uniform distribution is utilized because there is a broad absence of scientific agreement regarding the true distribution of these parameters; consequently, it is essential to investigate the entire solution space impartially. To assess energy autonomy, we isolate outcomes characterized by low importation rates for gas, liquid fuels (gasoline, diesel, and heating oil), and electricity. This process yields an uncertainty space S, comprising 2271 valid samples eligible for subsequent evaluation.

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Application of machine learning

In this phase, we deployed machine learning algorithms on S to extract latent information embedded within the solution space.

Pre-treatment

To diminish computational demands, the initial procedure involves refining the solution space S by discarding extraneous parameters. This includes certain auxiliary modeling variables—such as the annualization factor τ—which are present in the solution space but function merely as a derivative of two existing uncertain parameters; removing them prevents double counting. The second step aims to filter out low-variance outcomes, specifically where the standard deviation σi of the parameter fulfills the condition $\sigma_2^i \leq \epsilon$, $i \in \{1, \ldots, N\}$. Within this research, we establish $\epsilon = 0$ to exclude constant figures that bear no impact on the uncertainty evaluations. Furthermore, because the parameters constituting the solution space possess varying scales, units, and ranges—factors that hinder the direct deployment of machine learning algorithms—data standardization is executed via (4). In this context, X_i and denote the vector of samples without and with standardization, respectively, with $\mu_i = \frac{1}{M}\sum_j X_{j,i}$. This methodology is advantageous because it minimizes the apparent discrepancies among data of distinctive orders of magnitude by relying on relative values instead of absolute ones.

$$X_i' = \frac{X_i - \mu_i}{\sigma_i},\ i \in \{1, \ldots, N\}, \sigma_i > 0 \quad (3)$$

Clustering

Clustering represents a fundamental unsupervised machine learning technique designed to aggregate data points sharing comparable traits. This methodology is widely employed in statistical data analysis. In the current research, we utilize clustering and feature selection techniques for data mining, seeking to determine the most effective strategies to reach minimal or even negative carbon emissions while maintaining cost-effectiveness.

To accomplish this, the initial phase involves selecting a robust clustering algorithm. Because there is no a priori knowledge regarding the uncertainty space, three distinct clustering techniques were evaluated: K-means [45], Gaussian-mixture [46], and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) [47].

Assuming n samples $\mathbf{z} = \{zi,\ i = 1, 2, \ldots, n\}$ where every zi represents a multi-dimensional real vector, the K-means algorithm divides the n observations into k (≤ n) sets $\mathbf{S} = \{Sj,\ j = 1, 2, \ldots, k\}$ to minimize the within-cluster sum of squares, i.e.,

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{z} \in S_i} \|\mathbf{z} - \mu_i\|^2 = \arg\min_{\mathbf{S}} \sum_{i=1}^{k} |S_i| D(S_i) \quad (4)$$

Where μi and D indicate the mean and variance of Si. Alternatively, the Gaussian-mixture model identifies normally distributed subsets within a dataset. It optimizes the likelihood of the samples based on the model's parameters, as demonstrated in **Eq. 5** for multivariate data. In this context, ϕ represents the weight assigned to each mixture component.

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$$p(\mathbf{z}) = \sum_{i=1}^{K} \phi_i \mathcal{N}(\mathbf{z} \mid \vec{\mu}_i, \Sigma_i)$$
$$\mathcal{N}(\mathbf{z} \mid \vec{\mu}_i, \Sigma_i) = \frac{1}{\sqrt{(2\pi)^K |\Sigma_i|}} \exp\left(-\frac{1}{2}(\mathbf{z} - \vec{\mu}_i)^T \Sigma_i^{-1} (\mathbf{z} - \vec{\mu}_i)\right) \quad (5)$$
$$\sum_{i=1}^{K} \phi_i = 1$$

For DBSCAN, clusters are defined as areas of high density isolated by lower-density regions. This technique does not require specifying the expected number of clusters beforehand. Rather, the distance d between any two samples zi, zj, is governed by an ϵ constraint, as depicted in **Eq. 6,** provided there is a minimum number of samples required to establish a cluster.

$$d(z_i, z_j) \leq \epsilon, i \neq j \quad (6)$$

These three approaches embody standard clustering algorithms: centroid-based, distribution-based, and density-based clustering, respectively. The performance of each method was assessed and visualized in **Figure 4.**

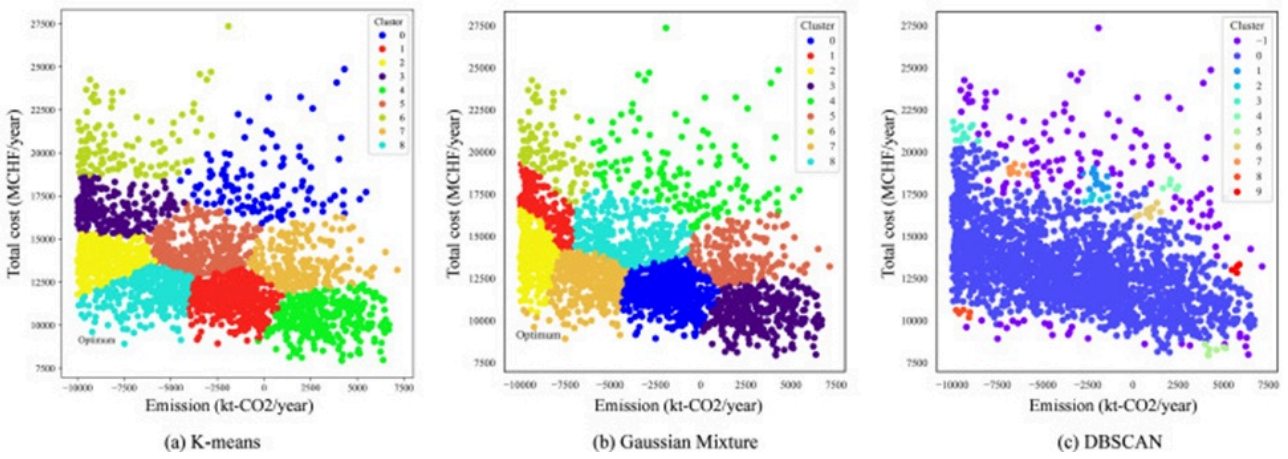


Figure 4. Clustering results by carbon emission (x-axis) and system cost (y-axis) via three representative clustering methods. Each dot in the figure represents a specific energy system configuration.

Feature extraction

The most favorable cluster is determined based on overall system costs and carbon emissions. Additionally, we seek to uncover latent characteristics within this cluster by examining the distribution of energy technology outputs and their mutual dependencies, which reflect the underlying technological correlations. Ultimately, the impact of primary technologies on reducing carbon emissions is quantified within the framework of an inherently uncertain system.

Results and Discussion

This section details the findings for Switzerland, incorporating all the previously discussed uncertainties.

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Comparison of clustering methods

Table 1 evaluates the three clustering techniques alongside their respective input parameters and silhouette scores [48]. The silhouette score serves as a quantitative measure for assessing performance, where a higher score indicates better clustering. The findings reveal that both K-means and Gaussian Mixture yield strong results. In contrast, DBSCAN produces a negative silhouette score, indicating it is ill-suited for clustering the uncertainty data in this context. This is true even though DBSCAN effectively isolates noise, as illustrated by Cluster −1 in **Figure 4**. Within the K-means and Gaussian Mixture models, Cluster 8 and Cluster 2, respectively, represent the optimal balance of economic and environmental factors. Importantly, adjusting specific parameters—such as the number of clusters for K-means or the eps (the maximum radius for two samples to be deemed neighbors) for DBSCAN—would likely alter these evaluation metrics. Additional experiments modifying DBSCAN's eps and minimum sample parameters demonstrated that the silhouette score s could be enhanced (for instance, achieving s = 0.54 with inputs of (0.5,10)). However, this configuration generates only two clusters, one of which is noise. While this yields a high silhouette score, a two-cluster outcome offers little value, as a primary goal of this research is to deeply analyze the low-cost, low-emission domain, a task requiring much finer clustering granularity. Consequently, all subsequent results rely on the K-means model outputs, which achieved the highest silhouette score.

Table 1. Input parameters and corresponding silhouette score for three typical clustering methods: K-means (centroid-based), Gaussian Mixture (distribution-based), and DBSCAN (density-based).

	DBSCAN	Gaussian mixture	K-means
Input parameter	(0.15, 5)[c]	9[b]	9[a]
Silhouette score	−0.27	0.24 – 0.31	0.36

[a]: Number of clusters; [b]: Number of components; [c]: (eps, min samples), with eps: ϵ-neighborhood.

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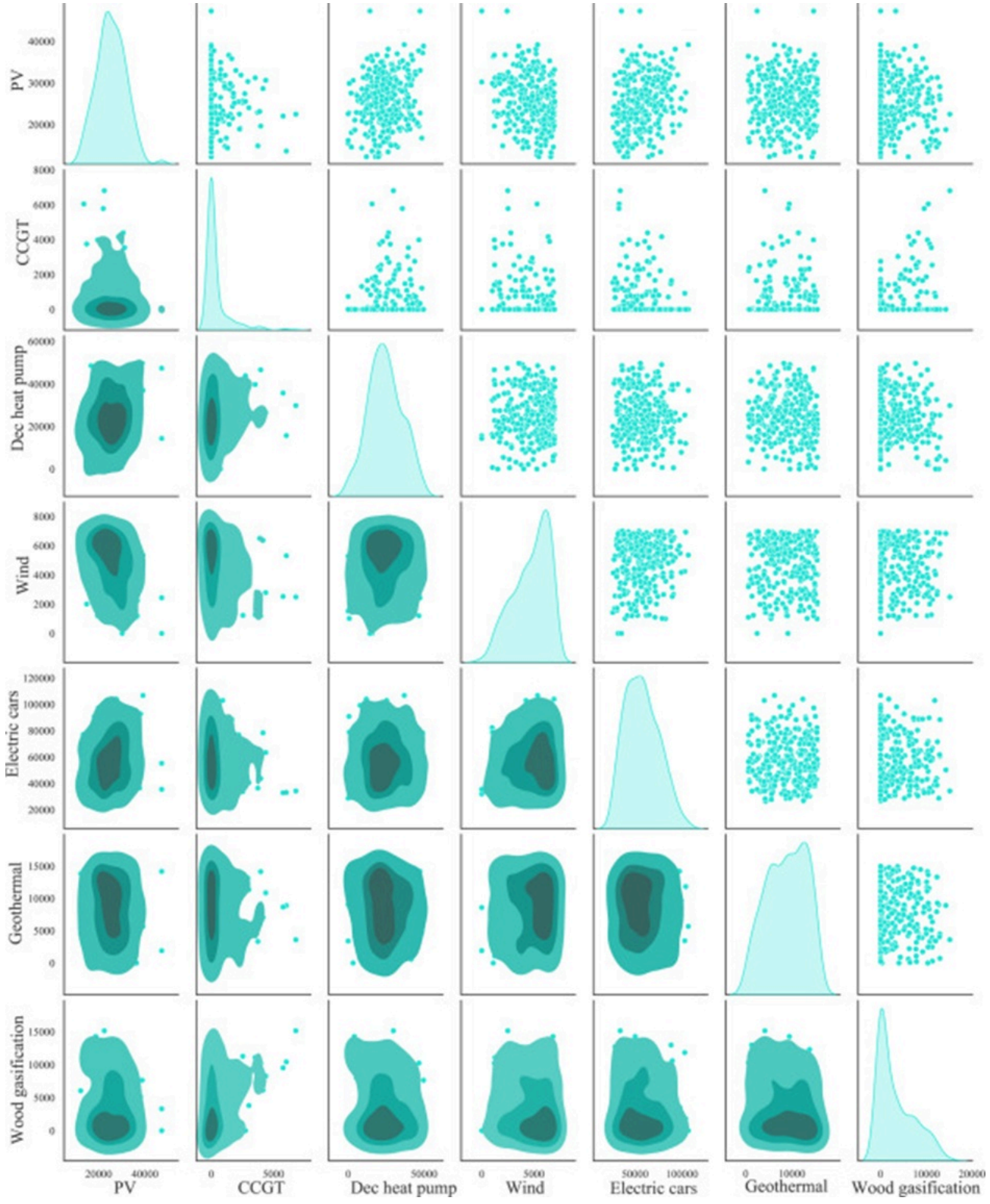


Figure 5. Single distributions and conditional distributions in the optimum scenario (Cluster 8 from **Figure 4**). Unit: GWh/year, except million passenger kilometer/year for Electric cars. CCGT stands for combined cycle gas turbine plant. Dec heat pump represents a decentralized heat pump. In the matrix: the diagonal shows the distribution of a single technology; the upper triangular illustrates the scattering of two technologies, and the lower triangular presents the distribution contour maps of the bilateral correlation of technologies.

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Results of feature extraction and analysis

Figure 5 displays the distribution outcomes of vital energy system technologies under the optimal scenario (Cluster 8) pinpointed via K-means. Within the matrix, the diagonal highlights the variance of individual technologies across the uncertainty space. Certain technologies exhibit minimal volatility; for instance, the peak for wind energy emerges near its projected capacity limit. Conversely, technologies like geothermal heat show broader fluctuations depending on the scenario. An alternative, insightful approach to examining energy technology distributions involves observing how they behave in relation to one another. This is depicted by the scatter plots in the upper triangle and the corresponding contour maps in the lower triangle, which feature four distinct density levels. The darkest shading indicates the most densely populated distribution areas. The findings demonstrate clear bilateral correlations for specific technological pairs. For example, PV and wind often exhibit an inverse relationship, where an increase in one is accompanied by a decrease in the other, likely due to competition between these two characteristic variable renewable sources. Similarly, PV and electric cars display a positive correlation.

Nevertheless, for many other technologies, clear conclusions remain elusive because their distributions indicate a scattered lack of dependence on one another. Advancing the analysis, technological correlations are measured using a coefficient ϱ ($|\varrho| \leq 1$). A value approaching 1 signifies a strong positive correlation between the technologies in question (e.g., a technology correlated with itself equals one). In contrast, −1 denotes a perfect inverse correlation, while zero suggests no relational bearing. **Figure 6** offers a heatmap detailing these correlations among essential components within the energy system's uncertainty space, allowing for two primary deductions:

- From the perspective of the technological contributions to carbon mitigation: the significance of various technologies in achieving decarbonization can be measured and subsequently ranked through this correlation analysis. Carbon capture and sequestration (CCS) displays a pronounced inverse correlation with carbon emissions. This is followed closely by PV, synthetic natural gas storage, wood gasification, and heat pumps. These results underscore the critical role these technologies play in achieving negative-emission objectives, suggesting they should be prioritized during the energy transition.
- From the perspective of the interaction between energy technologies:
    - Positive: the three most robust positive associations exist between wood gasification for synthetic natural gas and natural gas storage, PV & heat pumps, and hydrogen storage and carbon utilization (CCU). Given the opposing seasonal patterns of energy supply and demand in Switzerland, long-term storage will become increasingly crucial. Consequently, synthetic gas storage must grow in tandem with the widespread adoption of biomass gasification. In the second grouping, PV supplies the clean power required to operate heat pumps, leading to a prominent positive correlation. This logic extends to the third pairing, as hydrogen serves as a vital intermediary energy carrier for carbon utilization, acting as a feedstock to synthesize distinct fuels and plastics.
    - Negative: excluding the relationship between CCS and carbon emissions, the most notable inverse correlation occurs between industrial wood combined heat and power (CHP) and wood gasification for synthetic natural gas (SNG). This rivalry likely stems from the restricted availability of domestic wood resources (capped at roughly 15 TWh/year for sustainable application, referencing [49]). A further example of a negative correlation involves PV and geothermal power. In this case, geothermal energy proves less competitive than PV, presumably due to its comparatively steep expenses and lower conversion efficiency (approximately 8%, as cited in Ref. [50]).

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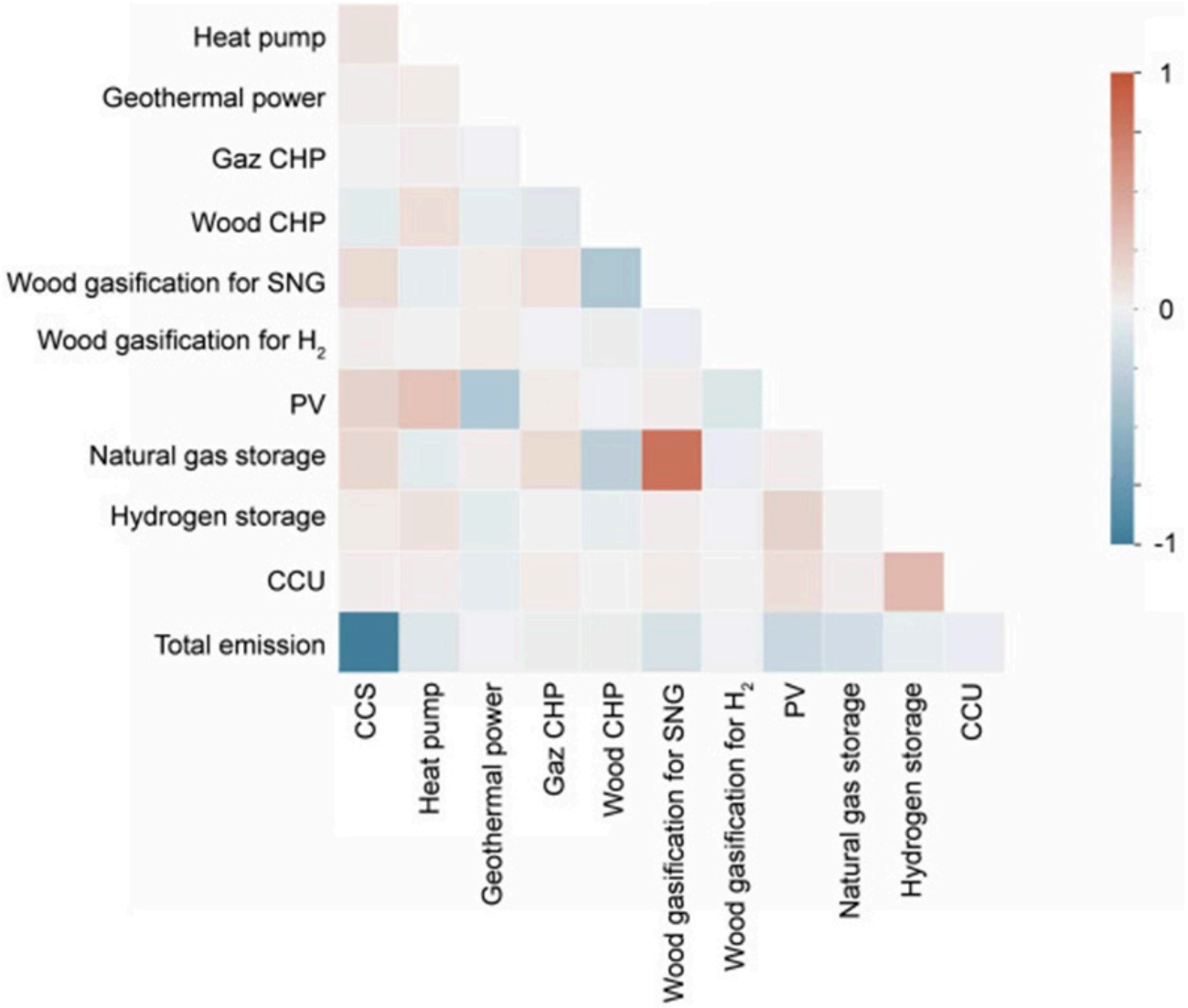


Figure 6. Quantification of correlations in the uncertain energy systems with multi-factor interactions. Positive values imply a positive correlation, while negative values imply a negative correlation. Zero implies irrelevance. Two aspects of the correlation: (a) mutual reaction among technologies; and (b) contribution of technologies to the total carbon emission (last line in the figure).

Discussion

By utilizing Monte Carlo simulations across diverse heterogeneous uncertainty factors, we established an uncertainty space that yields various optimized energy systems achieving negative emissions. Across different scenarios, the annualized total system cost fluctuates between 7500 and 27500 million Swiss Francs (CHF). As illustrated in **Figure 4**, the modeling outcomes indicate that under uncertain conditions, a low-emission system is not necessarily more costly than one with higher emissions. Nevertheless, interpreting these results further is challenging due to the intricate synergies and trade-offs among more than 100 interconnected technologies within the system. For instance, a reduction in the overall system cost could stem from decreased investments in specific technologies, lowered energy demands, a combination of both, or alternative factors. This highlights the vital need for a systematic uncertainty analysis, as proposed in this study, to prevent short-sighted decision-making. Consequently, the following sections will focus on evaluating the most critical uncertainty factors relevant to long-term energy planning.

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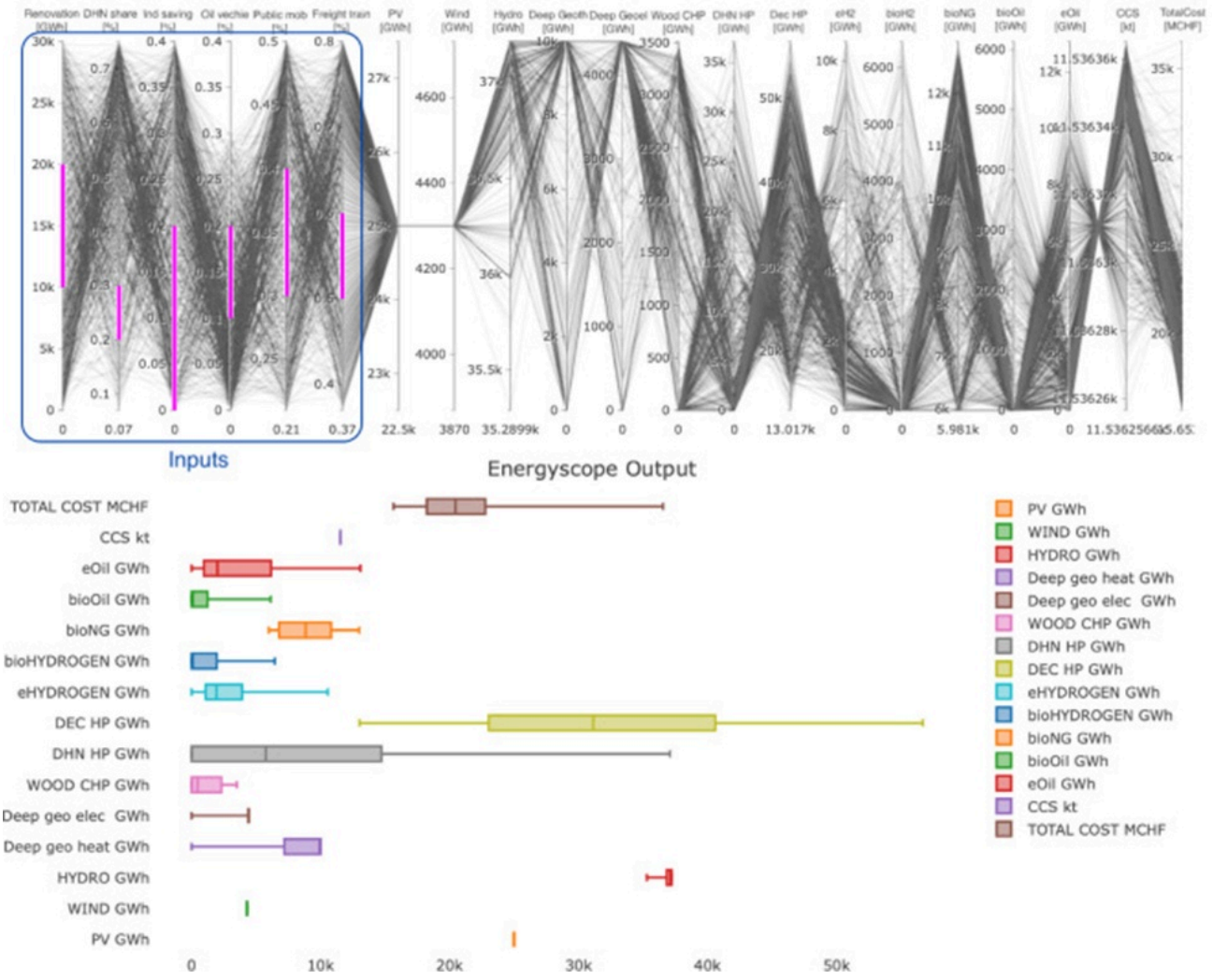
Sectorial Uncertainty Results

This section outlines findings derived from varying a specific subset of uncertainty parameters while holding the remaining parameters constant. This methodology allows for a clear interpretation of “local” uncertainties within particular sectors, thereby aiding decision-making for stakeholders in distinct domains. Three primary aspects were analyzed: (a) the impact of demand-side uncertainties; (b) the influence of uncertain domestic technology potentials; and (c) the effects of energy import uncertainties. For these analyses, the carbon mitigation objective is fixed at −6 MtCO2-eq for the year 2050 to neutralize irreducible emissions from non-energy sectors, particularly agriculture (which accounted for approximately 6 MtCO2-eq/year in 2020, as reported by FOEN [51]), thereby guaranteeing carbon neutrality across the entire society.

Uncertainty impact from energy efficiency improvement in demand side

Energy efficiency uncertainties encompass building renovation savings, the penetration of district heating networks (DHN) for low-temperature heat supply, industrial energy-saving potential (e.g., through heat recovery), the proportion of oil-based vehicles (reflecting the level of mobility electrification), the share of public transit in passenger transport, and the rail share in freight transport. All other parameters are maintained at their nominal values. Given the reduced number of variables, 1000 simulations were executed. The corresponding outcomes are depicted in **Figure 7.**

Within the parallel coordinates, each vertical axis represents either an uncertain input parameter or an optimized result. Infeasible configurations have been excluded.



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Figure 7. Uncertainty test result on the impact of energy efficiency on key areas in the Swiss energy system.

The upper portion of the figure displays the parallel coordinates encompassing all uncertain inputs and optimization outputs; the lower portion depicts the distribution of these results via a box chart, where the five vertical markers within each horizontal box signify the minimum, first quartile, median, third quartile, and maximum values of their respective ranges. The box chart reveals substantial uncertainty ranges for DHN and decentralized (DEC) heat pumps, demonstrating an inverse correlation predominantly dictated by the DHN market share. Biofuel and e-fuel production fluctuate across scenarios but generally remain between 0 and 15 TWh. Total system costs exhibit a relatively broad spectrum, ranging from 15 to 40 billion CHF/year. Notably, several technologies demonstrate robustness against uncertainty while meeting the −6 MtCO2-eq target—specifically PV, wind, hydro, and CCS. Consequently, these technologies should be prioritized during the decision-making process.

Uncertainty from domestic technology potential

The preceding uncertainty findings are predicated on the assumption that installed capacities for technologies can achieve their estimated limits. However, these limits are inherently uncertain themselves: any deviation would likely alter optimal investment and operational strategies. To assess how the energy system responds to varying penetration levels of PV, wind, biomass, waste, and geothermal energy, we applied the uncertain inputs detailed in **Figure 8**, assuming all other uncertainties remain at their baseline values.

The results indicate that fluctuations in the penetration of the aforementioned technologies critically shape the energy system's configuration. In scenarios characterized by minimal CCS utilization (indicated by the short purple vertical line on the CCS axis, near 10 Mt/year), fossil waste consistently remains at the lowest level. Because fossil waste is the primary driver of non-biogenic carbon emissions, its mitigation is a priority. Woody biomass is predominantly utilized for bioNG and bioOil production, alongside combined heat and power (CHP) generation, with very limited use for hydrogen gasification (bioH2). Instead, hydrogen is primarily generated via electrolysis (eH2), aligning with high PV penetration (exceeding 35 TWh/year). This dynamic highlights a potential competition between e-hydrogen and bio-hydrogen production. As further demonstrated in **Figure 9,** bio-hydrogen is only generated when PV output falls below 30 TWh/year, ranging between 0 and 5 TWh/year depending on the specific system configuration. A probable explanation is that surplus electricity from expanded PV capacity requires storage; with hydro storage reaching saturation, electrolysis serves as an effective power sink, producing storable hydrogen that can subsequently be transformed into other fuels. In situations where hydrogen is already produced on a large scale, wood is largely reserved for heat and power generation via CHP or for synthesizing alternative fuels, such as SNG or diesel.

In summary, while biofuel and e-fuel production varies by scenario, it consistently remains capped at 15 TWh/year. Centralized heat pumping appears less competitive than the direct application of deep geothermal heat, with a broad range of uncertainty. In contrast, decentralized heat pumping proves highly stable and sees significant demand. Furthermore, the volume of CO2 requiring annual sequestration remains consistent (10–15 Mt) irrespective of shifts in the system's technological mix.

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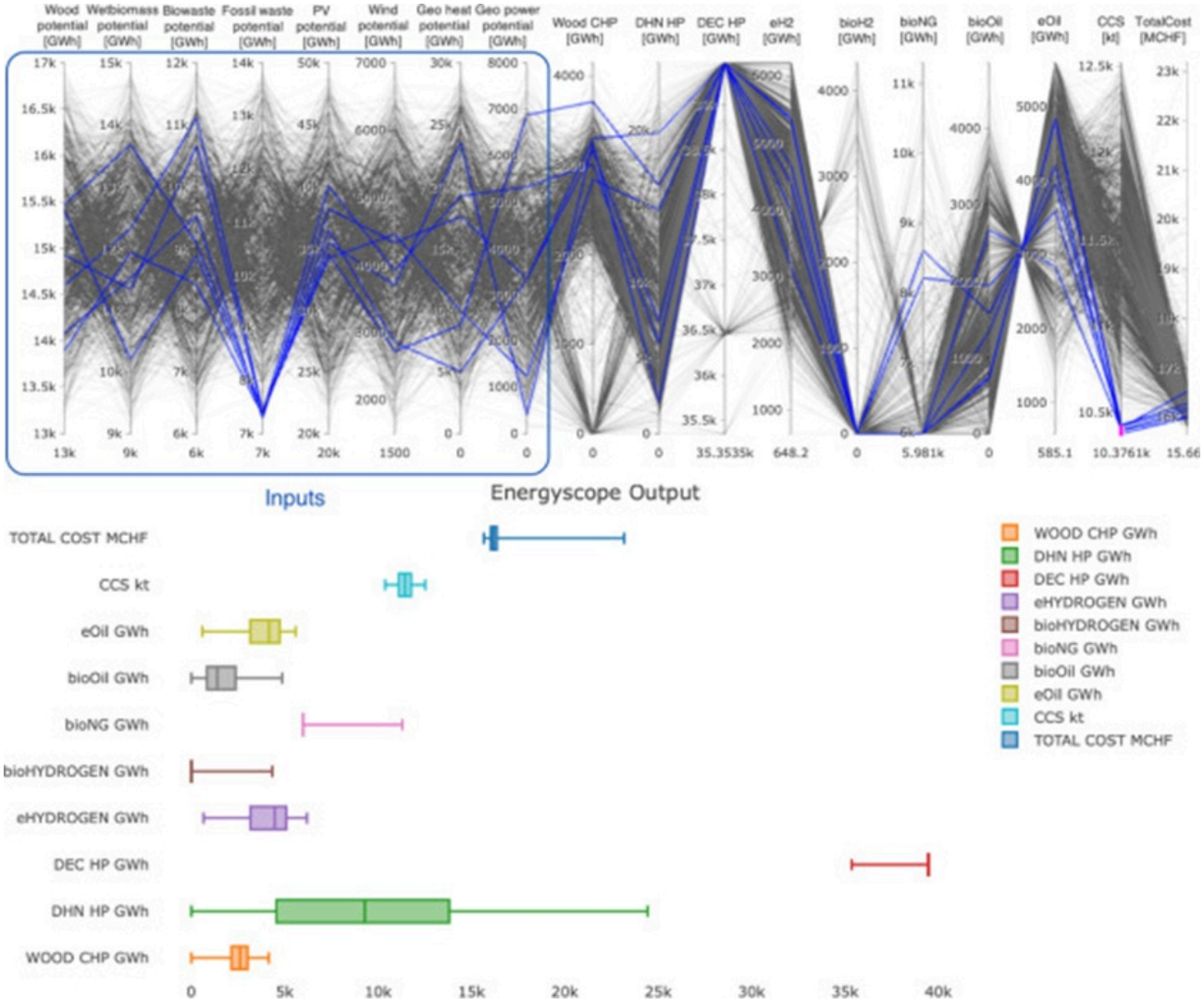


Figure 8. Uncertainty results: domestic resources' potential on technologies and system cost, assuming no fossil import in 2050.

All preceding analyses within this section operate under a zero-import assumption, demonstrating the viability of energy autonomy for Switzerland. Subsequently, we will investigate the influence of fuel costs on importation strategies.

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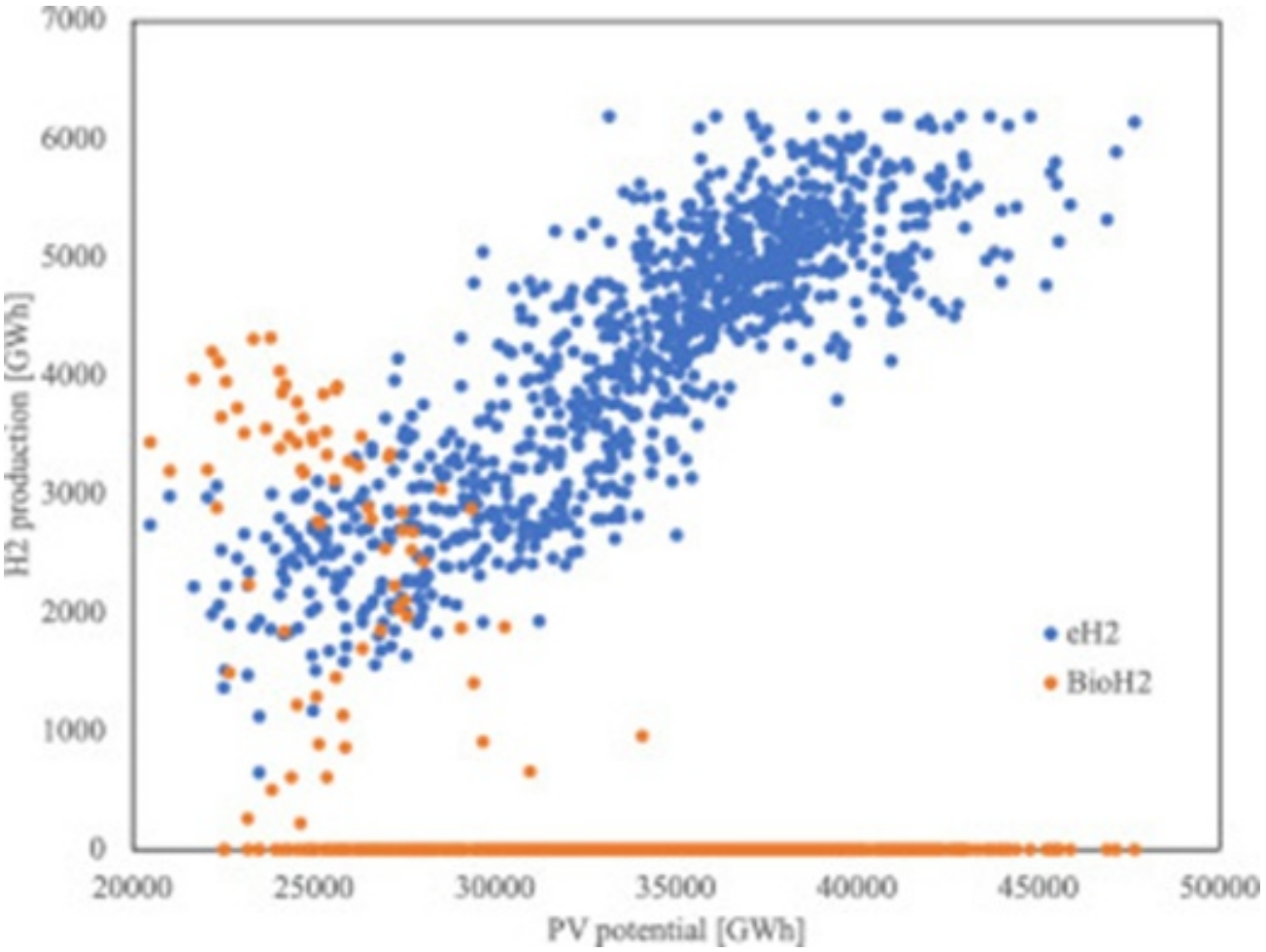
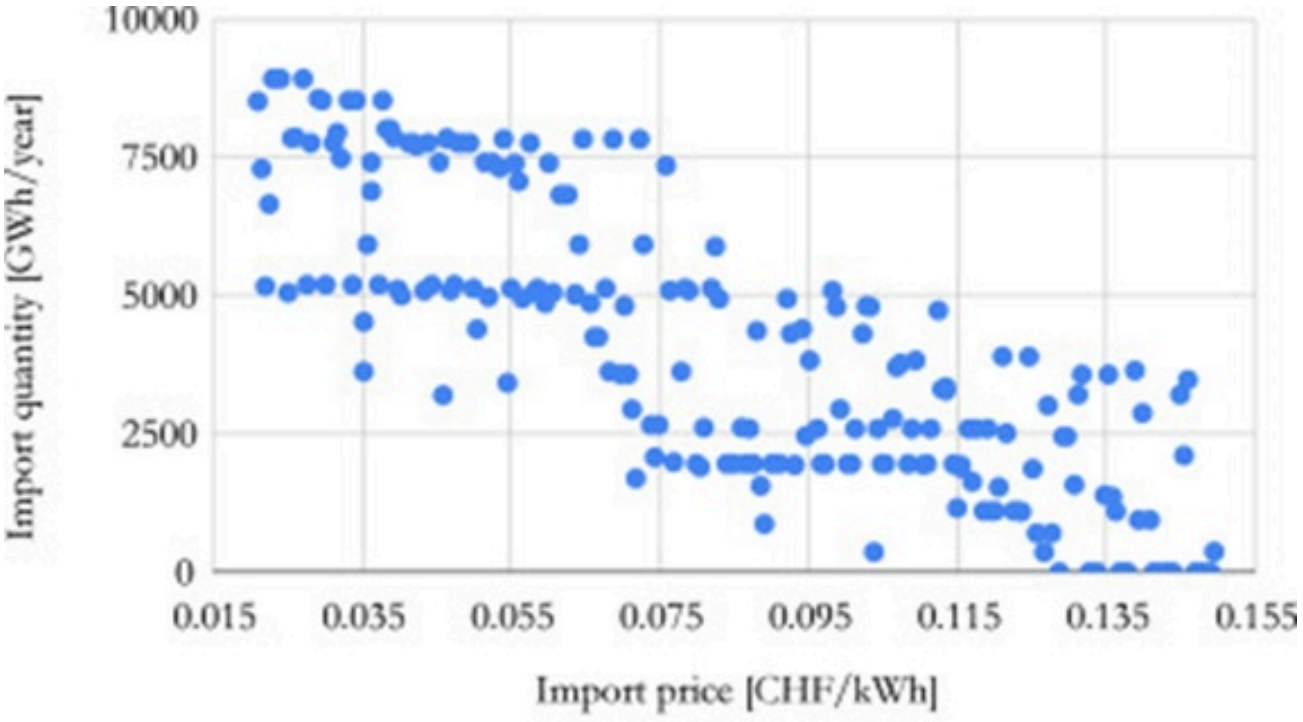


Figure 9. Uncertainty test results on hydrogen production from electrolysis (eH2) and biomass (BioH2) as a function of annual PV availability potential.

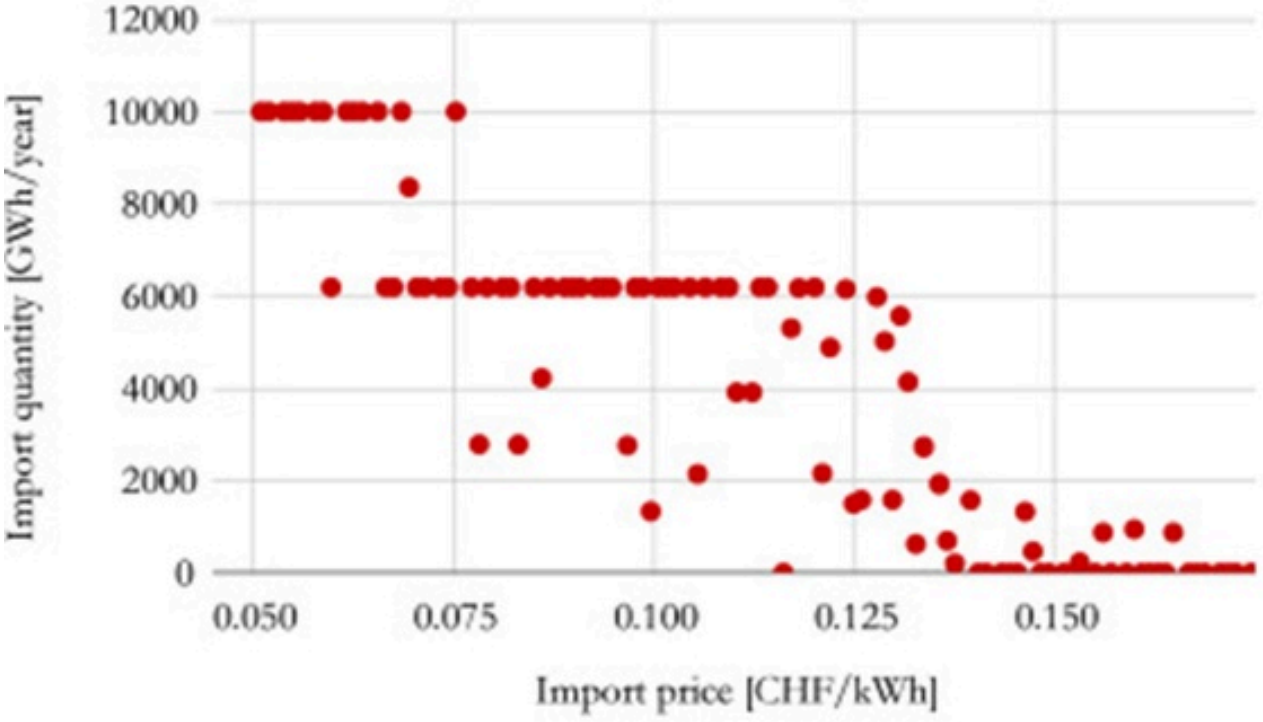
Uncertainty impact from energy importation

Given the strong momentum toward minimizing fossil fuel reliance in the wake of the Russia-Ukraine conflict, Switzerland will likely expand its share of imported green energy. This analysis considers the potential importation of electricity, SNG, and hydrogen by 2050. However, resource availability remains uncertain, as massive demand for biomass and hydrogen is anticipated in other nations by 2050, particularly within the EU. As noted in Ref. [52], fully decarbonizing the EU's energy sector would necessitate an 80% reduction in its gas consumption. Consequently, only a fraction of the available renewable gas potential would be accessible to Switzerland. Forecasting power imports is even more complex due to the growing intermittency associated with the widespread deployment of PV and wind power across EU countries. Thus, the long-term volume of foreign renewable resources available for Swiss importation involves profound uncertainty.

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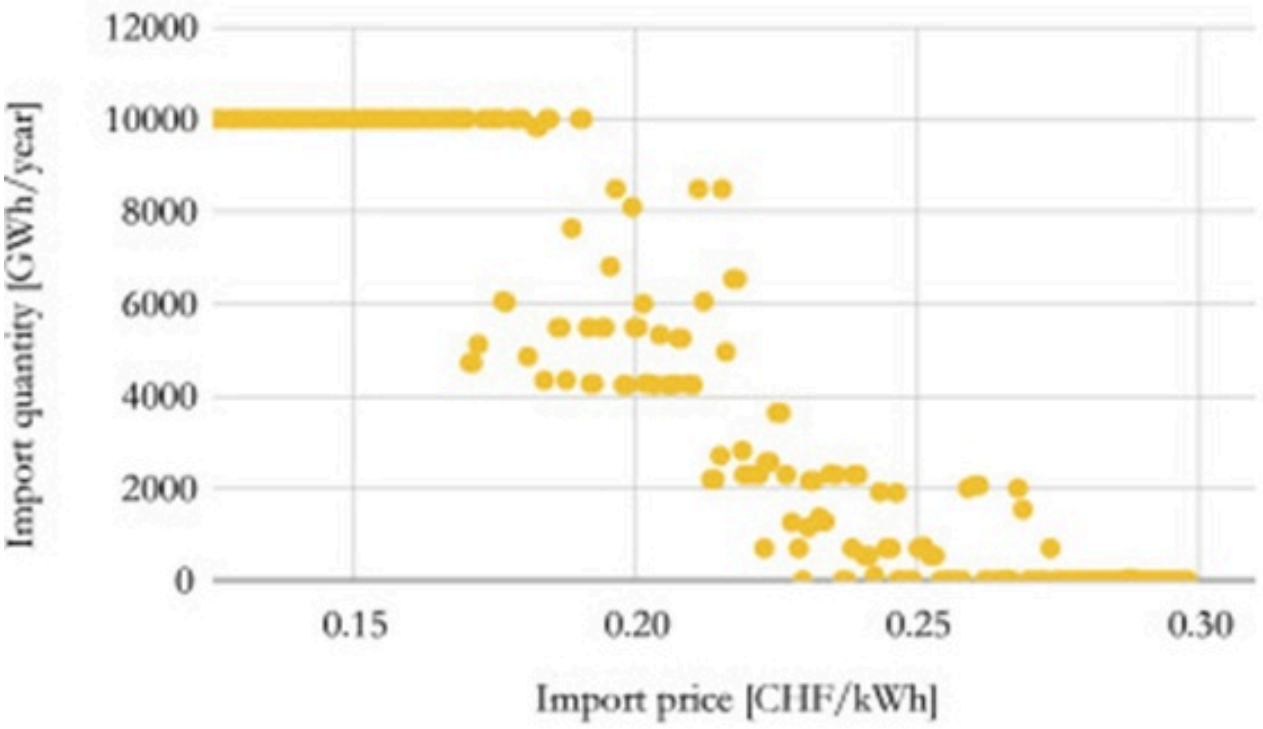


(a) Electricity



(b) Hydrogen

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(c) SNG

- Switzerland can achieve both energy independence and carbon neutrality by 2050, provided the supply system transitions to an almost 100% renewable foundation supported by carbon capture, utilization, and storage (CCUS) and sufficient infrastructural enhancements.
- Energy efficiency is a critical pillar of the energy transition. The reported data suggests that direct energy savings on the demand side hold as much significance as the construction of novel generation capacities. To reach this objective, prioritizing building retrofits, advancing industrial process designs, and electrifying the transport sector are paramount.
- On the supply side, photovoltaics (PV) for electricity generation, biomass for sustainable fuels, and geothermal energy coupled with heat pumps (HP) for thermal demands represent the most viable technologies slated for massive expansion. The first two consistently reach their maximum potential across nearly all evaluated scenarios, whereas deployment of the latter is heavily contingent on the extent of building renovations.
- Hydrogen is anticipated to serve as a crucial intermediary energy vector that enables robust sector coupling. Both electrolysis and biomass gasification are significant contributors to hydrogen generation. Furthermore, the prominence of electrolysis is projected to grow in tandem with higher rates of PV adoption.
- Attaining carbon neutrality in Switzerland by 2050 appears unfeasible without the extensive implementation of CCS (~10 million tons per year). This implies that the strategic planning of a CO2 infrastructure network must commence immediately. Key sectors for deploying these carbon capture systems include waste incineration facilities, biomass power plants, and the cement industry.

Conclusion

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This research challenges the traditional methodology of executing uncertainty analysis reliant on restricted scenario evaluations by introducing a comprehensive, systematic framework designed to examine highly interconnected and uncertain energy systems. Initially, we constructed an uncertainty space utilizing Monte Carlo simulations within the Energyscope model. Subsequently, machine learning algorithms were deployed across this space to uncover the dynamic interactions between fundamental energy technologies and to assess their respective impacts on carbon reduction targets quantitatively. Ultimately, probabilistic analysis was utilized to evaluate the ramifications of localized uncertainties.

This investigation helps resolve several complex questions that standard sensitivity analyses struggle to address. For example, **Figure 9** illustrates the respective roles of bio-hydrogen and e-hydrogen. At the same time, both are projected to be critical moving forward; the analysis identifies the specific conditions under which one variant captures a broader market share than the other. Policy formulation represents another vital domain for these applications, notably regarding nascent innovations like the biomass Fischer–Tropsch (FT) process utilized for bio-oil synthesis. Despite a consensus on its significance, virtually no nations have established definitive strategies for advancing the FT process [53-55]. The conditional distribution models introduced in this paper can assist in projecting the distribution and the most likely operational values for the FT process, contextualized within prospective policy frameworks governing PV and wind energy deployments. Consequently, this study fosters a deeper comprehension of the specific functions various energy technologies will fulfill throughout the systemic transition. Based on our findings, photovoltaic power generation, biomass-derived sustainable fuels, and heat pumps for efficient thermal management emerge as the most auspicious avenues for Switzerland's energy evolution. Notably, CCS and PV demonstrate the strongest inverse correlation with total carbon emissions. Given that these insights are derived from an extensive database of uncertainties, they are presumed to offer greater reliability than conclusions formulated from a constrained set of scenarios. Thus, the methodology proposed herein, which merges artificial intelligence techniques with uncertainty analysis, holds significant promise for widespread adoption in future energy planning frameworks.

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Conflict of interest

None

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None

Ethics statement

None

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