

Robust Multi-Criteria Optimization of a Residential Power–Heat–Hydrogen Polygeneration System: Integrating HOMER Scenarios with Monte Carlo–Fuzzy TOPSIS

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Abstract

This study aims to identify the optimal configuration of a polygeneration (power-heat-hydrogen) system at the residential scale through a case study of a 90 m² residential apartment in Tehran, Iran. The novelty of this study lies in integrating scenario simulation in HOMER with the Fuzzy TOPSIS multi-criteria decision-making framework and evaluating the robustness of the decision under uncertainty using Monte Carlo–TOPSIS. Four scenarios – PV-Grid, Grid, PV-Wind-Grid, and Wind-Grid – were evaluated based on the criteria of the levelized cost of electricity (COE), the levelized cost of hydrogen (COH), CO₂ emissions, and the share of renewable energy in electricity and heating. Fuzzy TOPSIS results indicated that Scenario 1 (PV-Grid) is the best option under both weighting policies, with a Closeness Coefficient (CC) of 0.99 in the Cost-priority policy and 0.98 in the Climate-priority policy. Scenario 3 (PV-Wind-Grid) ranked second, with CC values of 0.74 and 0.79. Scenarios 4 and 2 performed the worst, with CC values of approximately 0.11–0.13 and 0.02–0.06, respectively. Monte Carlo analysis reported a rank-1 probability equal to 0.99 for Scenario 1 and 0.01 for Scenario 3. Furthermore, the stability of Scenario 1 was confirmed with a very small interquartile range (IQR) (maximum 0.00475 at $\pm 50\%$) and a mean CC of 0.984738. The findings are applicable to system designers, researchers, and policymakers in the building sector for resilient decision-making.

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1 Introduction

The simultaneous growth in demand for electrical energy, thermal energy, and clean transportation fuels presents new challenges for energy systems at the building scale [1]. A high level of dependence on the electricity grid, fluctuations in the prices of energy carriers, and the intensification of environmental concerns associated with greenhouse gas emissions highlight the necessity of moving towards integrated energy systems based on renewable energy sources [2, 3]. In this context, the development of residential-scale CHP&H systems is emerging as an innovative solution that can simultaneously meet a building's electricity needs, provide heating, and supply clean fuel for hydrogen vehicles [4]. However, the diversity of configurations, economic uncertainties, and the variability of renewable resources transform the selection of the optimal option into a complex multi-criteria decision-making problem [5].

The importance of conducting such an investigation is particularly pronounced in Iran. As shown in Figure 1 [6], the current composition of the country's renewable energy portfolio is predominantly dominated by solar energy, with an installed capacity of photovoltaic (PV) systems of approximately 2633.7 MW representing a significantly higher share than other technologies. In comparison, the country's wind energy capacity is around 371.7 MW, and the contribution of technologies such as small hydropower (≈ 100 MW), expansion turbines (≈ 26 MW), and biomass (≈ 22 MW) in the renewable energy mix remains comparatively limited. This quantitative distribution suggests that, from the perspective of practical implementation, infrastructure availability, technology maturity, and market acceptance, solar energy is the dominant and most reliable renewable source in Iran, while wind energy primarily plays the role of a complementary source.

From a system-level analytical perspective, an approximately 7.1-fold difference in installed capacity between solar and wind power underscores the greater feasibility of solar-based scenarios for building-scale applications. This advantage stems not only from higher resource availability and superior technical potential but also from greater operational maturity and implementation experience, lower initial investment costs, and more straightforward grid integration [7]. Nevertheless, the substantial presence of wind energy in specific regions, particularly those surrounding urban centers, allows for its effective utilization as a complementary resource. Integrating solar and wind power can mitigate fluctuations in energy generation output, enhance

supply reliability, and reduce reliance on the electricity grid during peak-demand periods [7].

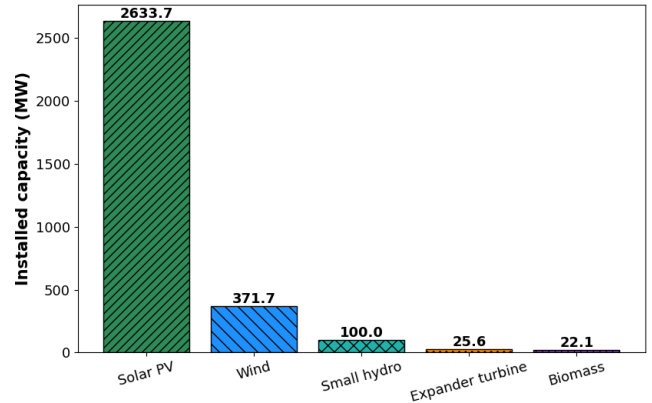


Fig. 1. Installed capacity of renewable power plants in Iran (as of November 2025)

Conversely, the limited national deployment of technologies such as biomass and expansion turbines suggest that, under current Iranian conditions, their economic viability for residential applications remains questionable. Consequently, grid-connected solar-wind systems emerge as the most technically justified and empirically supported options for designing integrated electricity-heat-hydrogen systems at the building scale. Solar and wind resources are inherently variable, and equipment and energy prices also fluctuate. In addition, stakeholders may have different priorities, such as economic or environmental concerns. Therefore, relying on a single scenario for energy planning or policy formulation risks suboptimal outcomes [8]. Therefore, a robust approach involves the simultaneous evaluation of multiple configurations incorporating solar, wind, and grid resources, coupled with a multi-criteria decision-making framework that accounts for inherent uncertainties. This enables the identification of stable and resilient solutions, preventing decisions from being overly sensitive to limited assumptions [9]. This methodology forms the core foundation of the technical, economic, and environmental analyses presented in this research.

Despite significant progress in the design and assessment of integrated renewable energy systems, a clear consensus regarding optimal configurations and key decision-making parameters remains elusive [10]. This highlights the need for a systematic and critical review of existing literature to identify knowledge gaps and limitations, thereby establishing a robust framework for the selection of appropriate methods, criteria, and scenarios in the present study.

Babatunde et al. (2024) [11] proposed a fuzzy multi-criteria decision-making framework to identify

the “optimal power system simulation software” for undergraduate education in developing countries. Data were gathered through questionnaires and expert elicitation from academic and industrial stakeholders (affiliated with Durban University of Technology (Durban, South Africa), University of Lagos (Nigeria), and The University of West Alabama (Livingston, AL, USA)). Eight commonly used software packages were evaluated against twelve criteria, with criteria weighting determined using fuzzy linguistic judgments. The Fuzzy-ARAS method was subsequently employed for scoring and ranking, identifying MATLAB as the superior option and MATPOWER (V8.0) as the least favorable. To validate the results, Fuzzy-TOPSIS was also implemented, yielding a divergent ranking (MATPOWER as the best and NEPLAN (V360 10.5.1) as the weakest). To reconcile these discrepancies, the authors proposed a combined coefficient, ultimately presenting a final ranking consistent with Fuzzy-TOPSIS, reaffirming MATLAB as the optimal choice and NEPLAN as the least favorable.

In 2025, Moradi et al. [12] evaluated the resilience and multi-criteria performance of renewable energy systems at the local scale, focusing on two sites in Algeria: Tamanrasset and Adrar. Their methodology involved scenario simulation in HOMER, followed by ranking using SAW and TOPSIS under six weighting scenarios, and a Monte Carlo uncertainty analysis with 5000 iterations. The results demonstrated that the solar option in Tamanrasset, with CO₂ emissions of 0, a levelized cost of energy (LCOE) of \$0.225/kWh, and a payback period of 0.29 years, consistently ranked first in five of six scenarios and maintained a superior performance in over 99% of Monte Carlo simulations. The Adrar option, utilizing a wind/diesel hybrid configuration, exhibited higher renewable energy generation (7425 vs. 4619 kWh/year) and lower losses (337 vs. 480 kWh/year) but proved less competitive economically and environmentally (initial cost \$5636 vs. \$3064, LCOE \$0.257/kWh, payback period 0.582 years, and CO₂ emissions of 86 kg/year).

Roy et al. (2025) [13] aimed to design and comprehensively evaluate (technically, economically, and environmentally) an off-grid hybrid renewable energy system incorporating hydrogen production, and to identify the optimal configuration under uncertainty. The study was conducted on the Isle of Eigg, United Kingdom. The methodology involved defining multiple system configurations comprising wind turbines (WTs), PV panels, diesel generators (DG), solid oxide fuel cells (SOFC), batteries, converters, proton exchange membrane electrolyzers (PEM), and hydrogen storage. Optimization was based on LCOE, followed by ranking using TOPSIS (with equal weights

of 16.67%), and then, an uncertainty analysis employing Monte Carlo simulations with up to 100,000 iterations. The results indicated that System A (WT/DG/FC/BAT/ELEC/CON/HT) was the most promising option, exhibiting the highest relative closeness to the ideal solution (0.88774) and minimal values for LCOE (\$0.1499/kWh), net present cost (NPC) (\$989,606.2), and levelized cost of hydrogen (LCOH) (\$45.2/kg), with CO₂ emissions of approximately 163,194.7 kg/year. Furthermore, the 90% confidence interval for NPC ranged from \$0.933–1.064 million, and for LCOE from \$0.1450–0.2109/kWh.

Shi et al. (2025) [14] sought to optimize and evaluate a city-scale wind-solar-hydrogen hybrid system designed to simultaneously meet electricity demand and provide clean fuel for transportation. The study was conducted in Lijiang City, Yunnan Province, China. The methodology involved system modeling and capacity optimization using HOMER Pro (v3.14.2), followed by multi-criteria ranking utilizing the Shannon Entropy-EDAS model to mitigate weighting bias. Several off-grid configurations were defined to identify the optimal solution, and a corresponding grid-connected configuration was subsequently developed. The chosen configuration included 5588 kW of PV capacity, an 800 kW wind turbine, a 1600 kW electrolyzer, a 421 kWh battery, and a 50 kW fuel cell. This system could supply approximately 200 households daily and produce 240 kg/day of hydrogen for buses, in addition to meeting the overall load. The results indicated that the off-grid system annually generates 10.15×10^6 kWh of electricity and 93.44 tons of H₂ (NPC = \$8.15 M, LCOE = \$0.43/kWh, LCOH = \$5.26/kg), while the grid-connected configuration demonstrated improved economic performance (NPC = \$7.34M, LCOE = \$0.11/kWh, and LCOH = \$3.42/kg).

Gao et al. (2025) [15] aimed to select and rank the most suitable renewable energy source for integration into a smart grid, considering uncertainty and expert judgment. A case study was conducted in Jiangsu Province, China. The methodology employed fuzzy TOPSIS, with data collected through questionnaires and the opinions of 25 experts (10 faculty members and 15 industry specialists). Four options – solar, wind, biomass, and hydropower – were evaluated based on five criteria: cost, energy efficiency, environmental impact, reliability, and scalability, using triangular fuzzy numbers. The fuzzy decision matrix was then normalized, the “fuzzy positive ideal solution” and “fuzzy negative ideal solution” were determined, and the “distance from the positive ideal” (d^+) and “distance from the negative ideal” (d^-) were calculated. For example, d^+ and d^- were 0.35 and 0.65 for solar, 0.28 and 0.72 for wind, 0.49 and 0.52 for biomass, and 0.40 and 0.60 for

hydropower. Finally, the “ C_i ” was extracted, revealing that wind energy ranked first with $C_i = 0.72$, followed by solar (0.65), hydropower (0.59), and biomass (0.48). Therefore, wind energy was identified as the superior option for smart grid integration, based on its proximity to the ideal solution and distance from the anti-ideal solution.

A comprehensive review of the literature reveals that numerous studies have assessed renewable and hybrid energy systems. However, many of these studies have been limited by a narrow scope. They have also failed to systematically account for economic uncertainties and resource variability, or to fully examine the interconnectedness of electricity, heat, and hydrogen at the building scale. Consequently, a key gap exists in the absence of an integrated framework for comparing multiple scenarios under technical, economic, and environmental criteria, with flexible weighting schemes. In response, the present study develops a hybrid framework based on precise system simulation and the application of multi-criteria decision-making methods, evaluating parameters such as energy cost, pollutant emissions, renewable energy share, reliability, and overall system performance under diverse scenarios, and explicitly analyzing the impact of weighting policies and uncertainty. The necessity of this research stems from the need to achieve stable, robust, and reliable decisions under the specific conditions prevailing in Iran, and the results can serve as a practical tool for researchers, energy policymakers, and energy system designers at the building scale to inform the selection and implementation of optimal configurations.

2 Study Location

This research uses a 90 m² apartment in Tehran, Iran, as the case study. The selection of Tehran is strategically significant due to its position as the nation’s primary energy consumption center within the build-

ing sector. Consequently, even modest reductions in grid reliance and increases in household renewable energy adoption have the potential to generate substantial cumulative impacts at both the urban and national scales [16]. Moreover, Tehran’s persistent air pollution and heightened environmental sensitivity underscore the compelling justification for evaluating low-carbon, integrated electricity-heat-hydrogen systems from both environmental and energy policy standpoints [17, 18].

Tehran’s climate is classified as semi-arid, characterized by pronounced seasonal variations with hot summers and cold winters [19]. This results in a bimodal energy demand profile, with heating requirements dominating during the winter months and cooling demands (and associated electricity consumption) peaking in the summer [20]. This dynamic necessitates the design of a flexible energy system capable of simultaneously addressing electricity and thermal loads, as well as producing hydrogen for fuel cell vehicles (e.g., the Toyota Mirai) [21]. The region’s abundant solar irradiance throughout much of the year supports the effective deployment of PV technology, while exploring wind power as a complementary resource can further mitigate grid dependency during specific periods [22].

Key characteristics of the study location, including geographical coordinates, altitude, solar radiation indices, air quality data, wind speed, and climate classification, are summarized in Table 1. This data is critical as it directly influences both the performance of renewable energy technologies and the building’s thermal and electrical energy demands. Specifically, solar radiation and ambient temperature impact PV generation and heating/cooling loads, while wind characteristics determine the reliability of wind power and its temporal correlation with solar production. Providing this detailed information enhances the transparency of the simulations, facilitates reproducibility of the results, and ensures the compatibility of the optimized scenarios with the specific conditions prevailing in Tehran.

Table 1. Climate, demographic, and location data for Tehran

Latitude	Longitude	Altitude (m above sea level)	Population	Average Annual Solar Radiation	Average Annual Clearness Index	Average Annual Wind Speed	Climate Type (Köppen-Geiger Classification)
35.42 N	51.18 E	1191 m	8.7 million (2025)	4.9 kWh/m ² ·day	0.593	5.26 m/s	Csa

3 Methodology

Figure 2 presents an integrated research framework that follows a systematic and sequential workflow for

the techno economic and environmental feasibility assessment of the proposed hybrid energy system. This framework is structured into three main operational phases:

Phase 1: System Simulation and Data Extraction (HOMER Software). In the first stage, various configurations of the grid connected solar-wind hybrid energy system – designed to meet electricity, thermal, and hydrogen demands – were modeled using HOMER. This phase concludes with the extraction of key technical, economic, and environmental performance indicators for each scenario.

Phase 2: Multi Criteria Decision Making (Fuzzy TOPSIS Method). In the second stage, the extracted indicators are processed using the Fuzzy TOPSIS method. This phase enables a comparative assessment and ranking of the modeled scenarios, identifying

the most resilient configuration based on predefined evaluation criteria.

Phase 3: Uncertainty and Resilience Analysis (Monte Carlo Method). Finally, Monte Carlo simulations are applied to the primary outputs. This phase rigorously evaluates the impact of input uncertainties, thereby validating the robustness of the decision making outcomes and ensuring the reliability of the selected optimal configuration. This sequential integration – from simulation, to multi criteria ranking, to uncertainty validation – establishes a comprehensive and reliable decision support process tailored to the case study of the residential complex in Tehran.

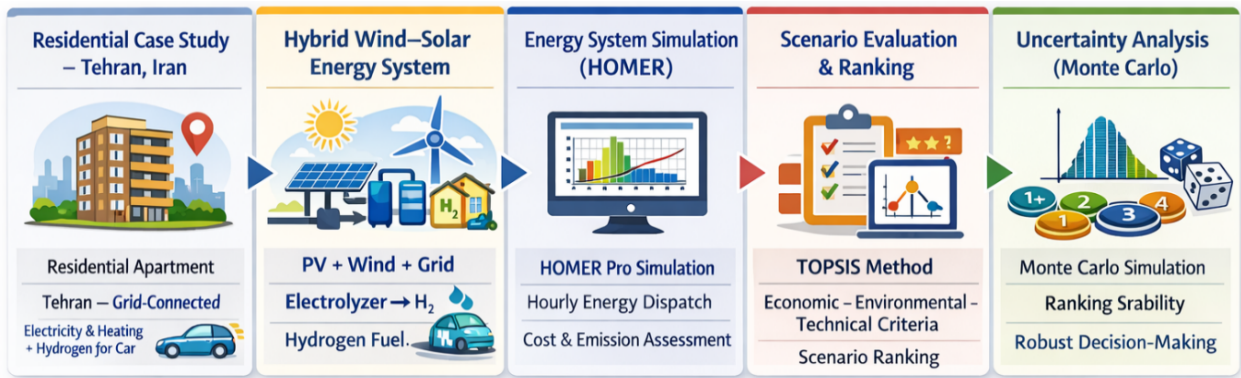


Fig. 2. Methodology framework for simultaneous electricity, heat, and hydrogen supply in a grid-connected residential building utilizing solar-wind energy.

In this research, HOMER Pro software was utilized solely as a tool for scenario generation and for extracting fundamental economic and technical indicators. Given the multi criteria nature of the problem, the outputs from HOMER (such as NPC, LCOE, LPSP, and CO₂ emissions) were integrated into a decision matrix processed via the Fuzzy TOPSIS method. This approach allows for explicit weighting of economic, technical, and environmental criteria and facilitates the modeling of uncertainty in decision maker preferences. In the subsequent step, to evaluate the robustness of the scenario rankings against fluctuations in input parameters (e.g., electricity prices, equipment costs, climatic conditions), the Monte Carlo-TOPSIS approach was employed. Thus, HOMER functions as the data generation engine, while the combination of Fuzzy TOPSIS and Monte Carlo-TOPSIS completes the multi criteria decision making process under uncertainty.

3.1 HOMER simulation

The physical and economic principles governing the system simulation within HOMER software are formal-

ized by the following set of equations. These equations facilitate a comprehensive evaluation of energy performance, hydrogen production, heat recovery, costs, and emissions, with the resulting outputs serving as direct inputs for the subsequent multi-criteria decision-making analyses (TOPSIS and Monte Carlo analysis).

At each time step t , the electrical power balance of the system is maintained as follows [22–24]:

$$P_{PV}(t) + P_{WT}(t) + P_{grid}(t) = P_{load}(t) + P_{EL}(t) + P_{dump}(t) \quad (1)$$

The equation states that the total power generated from solar, wind, and grid sources must meet the building's electrical load, the electrolyzer's power consumption, and the surplus power sent to the dump load. In this equation:

- $P_{PV}(t)$ is the output power of the PV system (kW).
- $P_{WT}(t)$ is the output power of the WT (kW).
- $P_{grid}(t)$ is the power exchanged with the grid (kW).
- $P_{load}(t)$ is the building's electrical load (kW).

- $P_{EL}(t)$ is the electrolyzer's power consumption (kW).
- $P_{dump}(t)$ is the dumped surplus power (kW).

The output power of the PV system at each time step is calculated as follows [25]:

$$P_{PV}(t) = P_{PV,nom} \times \frac{G(t)}{G_{STC}} \quad (2)$$

This equation shows the dependency of PV output power on solar irradiance and cell temperature. In this equation:

- $P_{PV,nom}$ is the nominal power of the PV system (kW).
- $G(t)$ is the instantaneous solar irradiance (W/m^2).
- G_{STC} is the irradiance under standard conditions ($1000 W/m^2$).

The output power of the WT is a function of wind speed [26]:

$$P_{WT}(t) = \begin{cases} 0 & \text{for } v < v_{ci} \\ P_r \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} & \text{for } v_{ci} \leq v < v_r \\ P_r & \text{for } v_r \leq v < v_{co} \end{cases} \quad (3)$$

In this equation:

- v is the wind speed at hub height (m/s).
- v_{ci} is the cut-in speed.
- v_r is the rated speed.
- v_{co} is the cut-out speed.
- P_r is the rated power of the turbine (kW).

The electricity consumption of the electrolyzer is determined based on the hydrogen production rate from Equation (4) [27]:

$$P_{EL}(t) = \frac{\dot{m}_{H_2} \times LHV_{H_2}}{\eta_{EL}} \quad (4)$$

In this equation:

- $\dot{m}_{H_2}$ is the hydrogen production rate (kg/h).
- LHV_{H_2} is the lower heating value of hydrogen (≈ 33.33 kWh/kg).
- η_{EL} is the electrolyzer efficiency (-).
- P_{EL} is the electrolyzer's power consumption (kW).

In the system under study in the present work, surplus electricity is converted to heat using Equation (5). This equation shows that surplus electrical power is converted into usable thermal energy with high efficiency [28]:

$$Q_{dump}(t) = \eta_{th} \times P_{dump}(t) \quad (5)$$

In this equation:

- Q_{dump} is the generated thermal power (kW).

- η_{th} is the efficiency of electricity-to-heat conversion.

The building's thermal balance is calculated through Equation (6) [29]:

$$Q_{Heat,load}(t) = Q_{dump}(t) + Q_{aux}(t) \quad (6)$$

In this equation:

- $Q_{Heat,load}$ is the building's thermal load (kW).
- Q_{aux} is the auxiliary heat (if there is a deficit) (kW).

Considering the limited capacity of recoverable heat from the electrical components (fuel cell, electrolyzer), the amount of recoverable waste heat was insufficient to play a significant role in meeting the residential unit's thermal load. Therefore, the only modeled thermal-electrical interaction was the conversion of surplus electrical power into heat via a Dump Load. In this approach, whenever electricity generation exceeded the instantaneous demand, the surplus energy was converted to heat and injected into the heating system. Since the heat generation logic is entirely dependent on electrical surplus, the coincidence factor of thermal and electrical loads is implicitly incorporated into the Dump Load operation, eliminating the need for independent modeling.

The only source of CO₂ emissions in this system is the electricity purchased from the grid. The emissions model (CO₂ Emissions) is calculated from Equation (7) [30]:

$$E_{CO_2} = \sum_t P_{grid}(t) \times EF_{grid} \quad (7)$$

In this equation:

- E_{CO_2} is the annual CO₂ emission (kg/year).
- EF_{grid} is the grid emission factor (kg CO₂/kWh).

Equations (8) and (9) are used to calculate the LCOE and the LCOH [31, 32]:

$$LCOE = \frac{C_{ann,tot}}{E_{served}} \quad (8)$$

$$LCOH = \frac{C_{ann,EL} + C_{elec}}{M_{H_2}} \quad (9)$$

In the above equations:

- $C_{ann,tot}$ is the total annualized cost (CAPEX + OPEX) (\$/year).
- E_{served} is the supplied electrical energy (kWh/year).
- $C_{ann,EL}$ is the annual cost of the electrolyzer (\$/year).
- C_{elec} is the cost of electricity consumed by the electrolyzer (\$/year).
- M_{H_2} is the annual hydrogen production (kg/year).

The electrolyzer was modeled with a constant efficiency of 85% (HHV) and a minimum operating load of 0%. This assumption represents a standard and valid simplification for hourly system level simulations, reflecting average operational efficiency. In modern electrolyzers, efficiency stability under partial load conditions, due to reduced ohmic losses, ensures high accuracy of model outputs over long term operation (25 years). Furthermore, the limitation of electrical efficiency in the hydrogen system is compensated through a heat recovery strategy within the polygeneration unit, whereby the generated thermal energy is utilized to meet a portion of the apartment's heating demand. Hydrogen leakage in modern storage systems is less than 0.1% per day and was therefore considered negligible in the hourly mass balance. Safety considerations and associated inspection requirements were incorporated into the system's operating and maintenance costs. The Renewable Fraction (RF) is calculated using Equation (10) [33]:

$$\text{RF} = 1 - \frac{E_{\text{grid}}}{E_{\text{tot}}} \quad (10)$$

In this equation:

- E_{grid} is the energy purchased from the grid (kWh/year).
- E_{tot} is the total energy consumed by the system (kWh/year).

In the dispatch configuration, both the Load Following and Cycle Charging strategies were activated, allowing the software's search algorithm to dynamically select the most economical strategy at each time step based on the load conditions and optimized component capacities.

3.2 Fuzzy TOPSIS method

In order to incorporate the uncertainty and ambiguity inherent in the decision making process, the Fuzzy TOPSIS method was employed, which is recognized as one of the most widely used fuzzy multi criteria decision making (MCDM) approaches [34]. In the present study, linguistic variables were used to represent uncertainty and subjectivity in the criteria evaluation process. These linguistic assessments were converted into Triangular Fuzzy Numbers (TFNs), selected for their computational simplicity, effectiveness in modeling the ambiguity of human judgment, and widespread applicability in fuzzy MCDM studies.

Five linguistic levels were utilized to express the relative importance of the criteria: Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). Each linguistic variable was mapped to a corresponding triangular fuzzy number as presented in Table 2, following the conventional structures commonly adopted in classical Fuzzy TOPSIS studies [35].

Table 2. Linguistic variables and corresponding triangular fuzzy numbers used in the Fuzzy TOPSIS method

Linguistic Variable	Triangular Fuzzy Number (l, m, u)	Interpretation
Very Low (VL)	(0.0, 0.1, 0.3)	Very low importance
Low (L)	(0.1, 0.3, 0.5)	Low importance
Medium (M)	(0.3, 0.5, 0.7)	Moderate importance
High (H)	(0.5, 0.7, 0.9)	High importance
Very High (VH)	(0.7, 0.9, 1.0)	Very high importance

Subsequently, fuzzy weights were assigned to the decision criteria in accordance with the adopted weighting policy (economy oriented or climate oriented), and the fuzzy decision matrix was constructed. The normalization and weighting procedures were performed following the standard Fuzzy TOPSIS methodology. The use of triangular fuzzy numbers allowed realistic modeling of uncertainty arising from expert judgment and ambiguity in the evaluation of criteria, thereby enhancing the robustness and credibility of the decision making process. The initial decision matrix, containing the raw values of each criterion for each scenario, was normalized to eliminate the impact of differing scales among criteria. Normalization was carried out as follows [36]:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (11)$$

where x_{ij} is the value of criterion j for scenario i , and r_{ij} is its normalized value.

In the Fuzzy TOPSIS method, fuzzy triangular weights are used instead of fixed weights to account for uncertainty in preference assessment [37]. A fuzzy weight is represented by a triangular fuzzy number $\tilde{w}_j = (l_j, m_j, u_j)$ for each criterion j , where l_j denotes the minimum, m_j the most probable, and u_j the maximum possible weight [38]. After applying the fuzzy weights, the weighted fuzzy decision matrix is obtained [39]:

$$\tilde{v}_{ij} = \tilde{w}_j \times r_{ij} \quad (12)$$

Distances to the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are then computed for each scenario [40,41]:

$$D_i^* = \sqrt{\sum_j (v_{ij} - v_{ij}^*)^2}, \quad (13)$$

$$D_i^- = \sqrt{\sum_j (v_{ij} - v_{ij}^-)^2}. \quad (14)$$

Finally, the closeness coefficient (CC) is calculated [42]:

$$CC_i = \frac{D_i^-}{D_i^- + D_i^*} \quad (15)$$

where a higher CC value indicates greater proximity to the ideal solution. After calculating the fuzzy distances, the fuzzy closeness coefficients were defuzzified using the Centroid (Center of Area) method due to its numerical stability, computational simplicity, and balanced representation of the TFN bounds. For a triangular fuzzy number $A = (l, m, u)$, the defuzzified value was calculated as:

$$\text{Defuzzified Value} = \frac{l + m + u}{3} \quad (16)$$

This process enabled the conversion of fuzzy closeness coefficients into crisp values, allowing the final ranking of scenarios.

In this study, the fuzzy weights employed within the Fuzzy TOPSIS procedure were directly derived from the Fuzzy AHP model, ensuring methodological consistency between the weighting and ranking stages. To achieve accurate and unbiased weighting, the criteria weights were determined using the Fuzzy AHP model based on the consensus of five distinguished experts in the fields of energy systems, energy economics, and environmental science. Expert pairwise comparisons were represented using triangular fuzzy numbers to minimize uncertainty in human judgment. These linguistic variables were aligned with those used in the Fuzzy TOPSIS framework, thereby ensuring full coherence across the weighting and decision making processes. Furthermore, to validate the robustness of the resulting rankings, a comprehensive sensitivity analysis was performed on the criteria weights to confirm that the optimal scenario remains stable across a broad range of policy priorities (economic versus environmental).

3.3 Monte Carlo method

To assess the impact of uncertainties in criterion weighting and system performance, a Monte Carlo-TOPSIS framework was employed. The decision matrix comprised four energy supply options (scenarios)

evaluated against five criteria: three cost-based (LCOE in \$/kWh, LCOH in \$/kg H₂, and CO₂ emissions in kg/year) and two benefit-based (renewable energy fraction for electricity and heating).

In the present study, the Monte Carlo-TOPSIS analysis was performed using 5000 independent iterations to ensure the statistical stability of the results and the reliability of scenario rankings under uncertainty conditions. The selection of 5000 iterations was based on previous studies and preliminary convergence tests, indicating that further increases in the number of iterations did not produce significant changes in the mean CC or in the probability of scenarios achieving the first rank.

To generate random parameters, a uniform random sampling method was applied. In each iteration, the criteria weights and system performance parameters were independently sampled within the predefined uncertainty ranges. The weights were then normalized, and the complete TOPSIS procedure – including normalization of the decision matrix, construction of the weighted decision matrix, determination of the positive and negative ideal solutions, and calculation of the CC – was executed.

To assess the convergence of the results, variations in the mean CC values and scenario rankings were evaluated throughout the simulation process. The results indicated that after approximately 3000 iterations, the changes in the mean CC values for all scenarios became negligible, and the results reached statistical stability. Therefore, 5000 iterations were selected to ensure convergence and reduce the final statistical error, thereby confirming the adequacy of the results and the reproducibility of the analysis.

In each Monte Carlo iteration, the TOPSIS method was fully executed. This process included vector normalization of the decision matrix, combination with weights, and determination of the positive ideal solution (PIS) and negative ideal solution (NIS). Euclidean distances from these reference points were then calculated. Subsequently, the CC was calculated for each scenario. To incorporate uncertainty, two levels of noise were applied:

- *Uncertainty in Weights:* Criterion weights were simultaneously varied in each iteration using a uniform distribution within the range $[1-L, 1+L]$ around the base weights (initially equally assigned to all criteria), where L represents the level of uncertainty. For uncertainty levels of $\pm 10\%$, $\pm 20\%$, $\pm 30\%$, $\pm 40\%$, and $\pm 50\%$, weights were randomly altered and then normalized. In this study, uncertainty in criteria weights was modeled using a uniform distribution so that all values within the defined uncertainty range had equal

probability of occurrence. This choice was made due to the absence of precise statistical information regarding decision-makers' preferences and to avoid introducing bias into the weighting process. Furthermore, for the performance parameters including COE, COH, and CO₂, lognormal noise was applied, as this type of distribution is more suitable for modeling economic and energy parameters that exhibit non-negative behavior and asymmetric variability.

- *Uncertainty in System Performance:* Lognormal noise [43] was applied multiplicatively to cost and emission criteria (COE, COH, and CO₂), constraining values within a logical range of $[1 - \delta, 1 + \delta]$ to avoid negative values. Noise levels of $\pm 25\%$ were applied to costs and emissions, while renewable criteria (RFs) were subjected to $\pm 10\%$ noise. In each iteration, a new decision matrix was generated based on these applied noises and weights, and the CC index was recalculated. The results were presented as Box plots illustrating the distribution of CC for each scenario and uncertainty level. Each panel depicts the CC value distribution for different scenarios, highlighting the impact of uncertainty variations on scenario rankings.

To ensure the stability of the Monte Carlo results, the convergence behavior of the CC index throughout the iterations was examined. The convergence analysis indicated that the mean and standard deviation of CC for all scenarios became nearly constant after approximately 3000 iterations, and statistical fluctuations were minimized. This finding confirms the adequacy of the selected number of iterations and the reliability of the results obtained from the uncertainty analysis.

The IQR, representing the range between the first and third quartiles, quantifies data dispersion around the median [44]. This index provides a robust measure of data stability, unaffected by outliers, and is widely used in uncertainty analyses. IQR is calculated as:

$$\text{IQR} = Q_3 - Q_1 \quad (17)$$

Where Q_1 represents the first quartile (25th percentile) and Q_3 represents the third quartile (75th percentile). The IQR was examined to evaluate the dispersion of Monte Carlo simulation results and assess the stability of the multi-criteria decision-making process [45, 46]. A small IQR indicates data concentration around the median, signifying high result and ranking stability. Conversely, larger IQR values suggest increased sensitivity to uncertainties and greater performance fluctuations [47]. Furthermore, IQR facilitates outlier identification, defining values outside the range $[Q_1 - 1.5 \times \text{IQR}, Q_3 + 1.5 \times \text{IQR}]$ as outliers [48]. The use of IQR

in this methodology enables a quantitative assessment of TOPSIS result stability and a reliable comparison of scenarios under uncertainty [49].

4 Input Data

The input data for this research encompasses climatic information (Table 1), the building's electrical, thermal, and hydrogen load profiles (Figure 3), equipment specifications, and economic assumptions (Table 3). Climatic data, including solar radiation, wind speed, and ambient temperature, was sourced from reliable databases and utilized on an hourly or monthly basis for system performance simulations. The building's electrical load was defined based on the consumption pattern of a typical residential unit, while the thermal load was determined considering climatic conditions and building heating requirements.

Technical parameters of the equipment – including solar panel and WT specifications, electrolyzer efficiency, hydrogen storage tank capacity, and thermal system characteristics – were incorporated into the model. Economic data, such as investment costs, operation and maintenance costs, and grid energy prices, were considered key inputs for the optimization process. Data selection prioritized realism while enabling a fair comparison of scenarios and a sensitivity analysis of the results.

To ensure the practical feasibility of installing renewable energy systems in dense urban environments, maximum capacity constraints were imposed on renewable components within the HOMER optimization model. As shown in Table 2, the maximum capacity of both solar and wind systems was limited to 10 kW. This constraint reflects the available rooftop area for PV installation in a typical residential unit with an approximate floor area of 90 m² in Tehran, as well as urban limitations associated with the installation of small-scale wind turbines, including noise and vibration considerations.

Table 4 presents the pollution penalty prices and corresponding emission factors for the two primary emission sources – Grid and Boiler. These values are used to convert emissions into an “environmental cost equivalent” for comparison alongside economic indicators. In the calculations, the emission of each pollutant is determined by multiplying energy/fuel consumption by its emission factor, which is then multiplied by the penalty price to calculate the corresponding environmental cost. The emission factors for the Iranian grid electricity were assumed to remain constant over the project lifetime, as accurately predicting future changes in the country's electricity generation mix is subject to significant uncertainty.

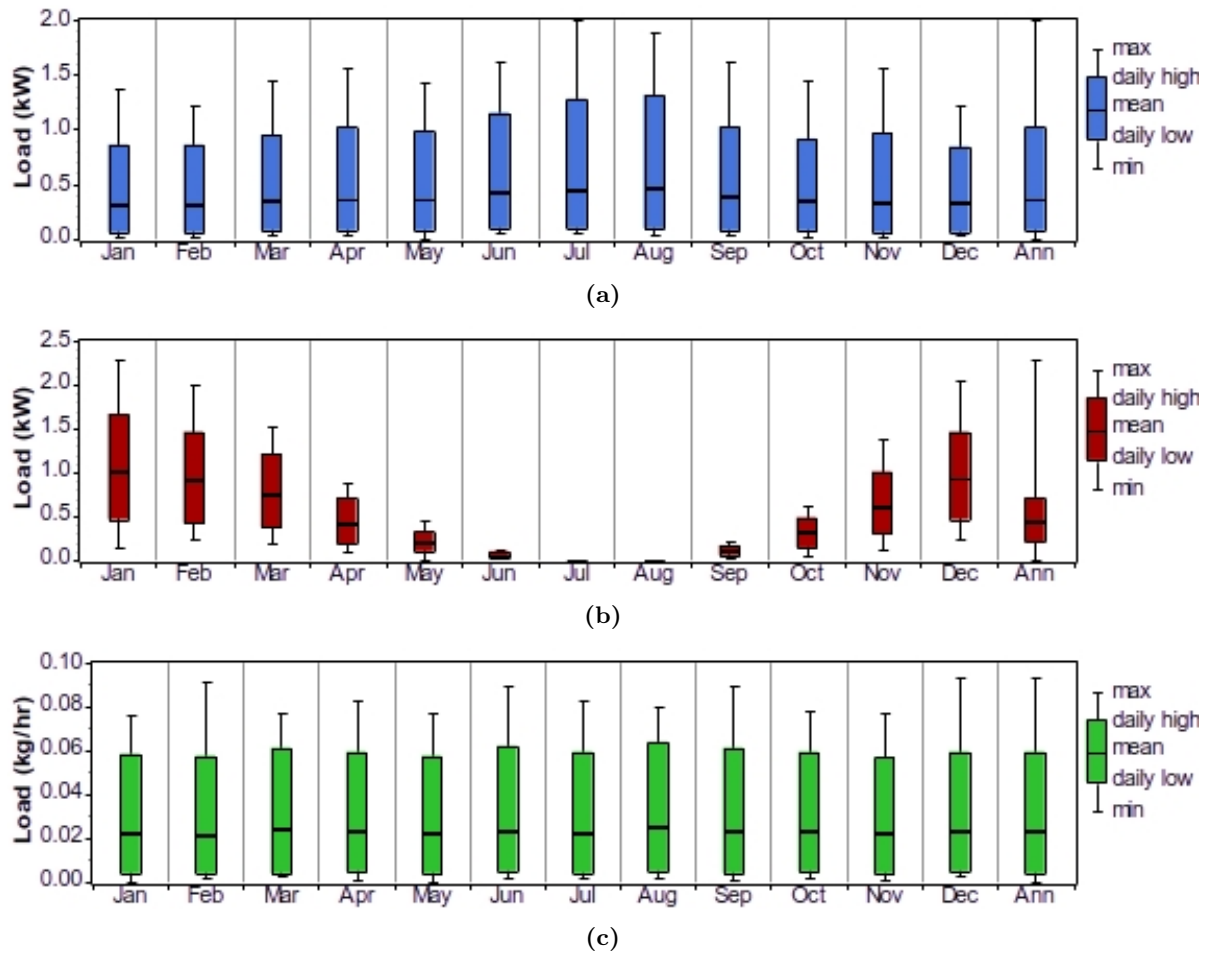


Fig. 3. Annual load profiles for the apartment: (a) Electricity, (b) Heat, (c) Hydrogen.

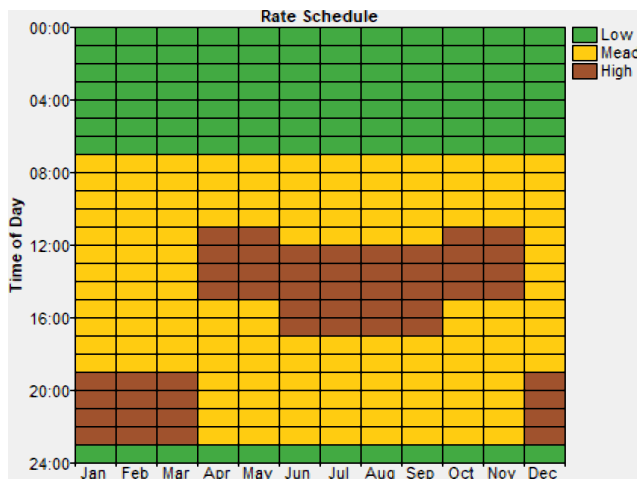
Table 3. Input data used in the HOMER software

Equipment	Capital (\$)	Replacement (\$)	O & M (\$/hr)	Size to consider	Other information
PV [50]	350	350	10	0-10	Lifetime: 25 years, Derating factor: 80%
Generic 1 kW WT [51]	850	850	10	0-10	Lifetime: 20 years, Hub height: 17 m
Converter [50]	138	138	10	0-10	Efficiency of inverter/ rectifier 95/85, Lifetime: 15 years
Electrolyzer [51]	500	250	10	0-5	Efficiency: 85%, Lifetime: 20 years, Minimum Load Ratio: 0%
Hydrogen Tank [51]	574	574	10	0-2	Lifetime: 25 years

Table 4. Pollution penalty prices and corresponding emission factors for grid electricity and the boiler in the environmental assessment model.

Type	Boiler [52]	Grid [53]	Penalty price (\$/ton) [54]
CO ₂	-	632 g/kWh	30
CO	6.5 g/L	-	-
Unburned hydrocarbons	0.72 g/L	-	900
Particular matter	0.49 g/L	-	45000
Fuel sulfur converted to PM/SO ₂	2.2%	2.74 g/kWh	18000
NO _x	58 g/L	1.34 g/kWh	20000

Figure 4 illustrates the times corresponding to the three-tiered electricity tariff (off-peak, mid-peak, and on-peak) throughout the year. Electricity purchase prices from the grid during these periods are set at \$0.0005, \$0.001, and \$0.0025 per kWh, respectively. The selling price of electricity back to the grid is considered to be \$0.044 per kWh, based on the average price on the Green Energy Stock Exchange.

**Fig. 4.** Temporal map of the three-tiered electricity tariff throughout the day and across different seasons of the year.

In this study, an annual real interest rate of 23% [55] was assumed, with a project lifespan of 25 years [56, 57]. The price of diesel fuel was set at \$0.006 per liter [58], and boiler efficiency was assumed to be 85% [52].

In this study, to guarantee system reliability, capacity shortage was not allowed in the optimization process; therefore, the “Loss of Power Supply Probability (LPSP)” index was effectively assumed to be zero. In the grid connected configuration, the utility grid serves as the backup source, compensating for any power deficit when renewable generation is insufficient. Under grid outage conditions, due to the absence of an energy storage system, the proposed configuration is unable to supply the electrical loads – including critical loads – and its reliability is therefore fully dependent

on the stability of the national grid.

For the economic evaluations, a real annual discount rate was applied. This rate was determined based on the actual conditions of Iran’s financial market to incorporate the effects of inflation and the risks associated with currency depreciation throughout the 25 year project horizon. Using this real rate ensures that all capital and operational costs are assessed in terms of constant monetary value, providing a conservative and technically rigorous basis for evaluating the project’s economic performance.

5 Results

In the present study, the adopted approach is based on the systematic screening of all possible combinations within the search space of the problem. To identify the optimal configuration, every feasible combination of distributed generation resources (including PV, wind, and grid connection options) was subjected to a comprehensive techno economic evaluation. The four selected scenarios represent the final outputs of the optimization algorithm, which – after comparing the performance of all possible configurations based on the objective functions and technical constraints – demonstrated the highest levels of efficiency and operational stability. Figure 5 (Comparison of TOPSIS Closeness Coefficient) and Figure 6 (Probability of Achieving Rank 1) present the results of the Monte Carlo-TOPSIS method under various uncertainties in weights and performance parameters.

Under both cost- and climate-priority weighting schemes, Scenario 1 (PV-Grid) consistently achieved the highest rank and demonstrated the closest proximity to the ideal solution. The CC was 0.99 under cost prioritization and 0.98 under climate prioritization, indicating a remarkably stable performance for this scenario. Scenario 3 (PV-Wind-Grid) consistently ranked second, with CC values of 0.74 and 0.79 for cost and climate prioritization, respectively. This improvement under climate prioritization reflects the increased weighting of renewable energy criteria and the corresponding stronger performance of the combined PV-

Wind system. Scenarios 4 (Wind-Grid) and 2 (Grid) exhibited significantly lower CC values (0.11/0.13 and 0.06/0.02, respectively), indicating comparatively poor performance.

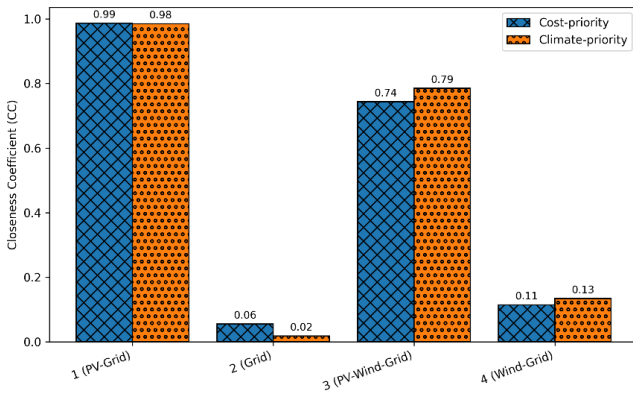


Fig. 5. Comparison of the CC obtained from the Fuzzy TOPSIS method under economic-priority and climate-priority weighting policies.

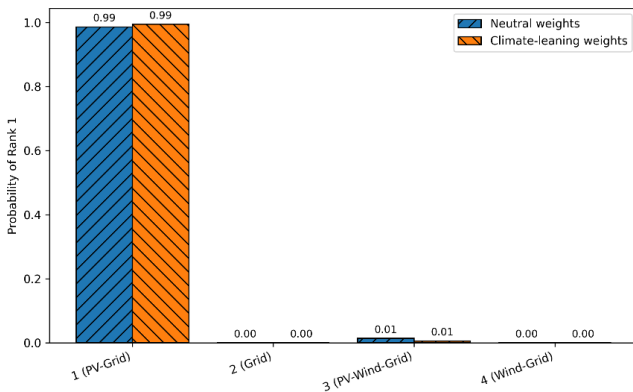


Fig. 6. Probability of scenarios achieving the first rank based on Monte Carlo analysis using the TOPSIS method under neutral and climate-oriented weighting distributions.

Analysis of the probability of achieving rank 1 (Figure 6) further reinforces these findings. Scenario 1 (PV-Grid) demonstrated a very high probability of 0.99 under both weighting schemes, highlighting its robustness. Scenario 3 (PV-Wind-Grid) exhibited a low probability of 0.01, indicating greater sensitivity to weight variations. Scenarios 2 (Grid) and 4 (Wind-Grid) had probabilities approaching zero, signifying fundamental weaknesses in their configurations.

Qualitatively, Scenario 1 (PV-Grid) emerges as the optimal solution, consistently outperforming all others under both cost and climate prioritization. This demonstrates its versatility and desirable performance from both economic and environmental perspectives. Scenario 3 (PV-Wind-Grid) performs well due to the

synergy of solar and wind energy but exhibits greater sensitivity to changes. Scenarios 4 (Wind-Grid) and 2 (Grid) consistently underperform, reflecting inefficient renewable energy utilization or excessive reliance on the grid.

In conclusion, Scenario 1 (PV-Grid) demonstrates consistent and stable performance based on both CC comparison and rank probability. Scenario 3 (PV-Wind-Grid) is more sensitive but still outperforms Scenarios 2 and 4. Scenarios 2 (Grid) and 4 (Wind-Grid) are significantly weaker and achieve rank 1 with negligible probability.

The IQR values of the TOPSIS Closeness Coefficient (Table 5) reveal distinct performance stability characteristics under uncertainty. Scenario 1 (PV-Grid) exhibits the lowest IQR values across all uncertainty levels, with a maximum of 0.00475 at $\pm 50\%$. This indicates a high concentration of CC values around the median and strong decision stability. This suggests that even with simultaneous variations in criterion weights and performance parameters, the proximity of this scenario to the ideal solution remains remarkably constant. Conversely, Scenario 3 (PV-Wind-Grid) displays the highest IQR values, increasing from 0.01869 at $\pm 10\%$ to 0.09429 at $\pm 50\%$, signifying greater sensitivity to uncertainties, although it remains superior to Scenarios 2 and 4 in average CC. Scenario 4 (Wind-Grid) exhibits moderate IQR values, indicating limited stability and greater parameter dependence. Finally, Scenario 2 (Grid), despite a relatively small IQR, consistently resides near the anti-ideal solution, indicating stable but poor performance.

Overall, the IQR analysis confirms that Scenario 1 is not only the best option based on average CC but also the most robust. Scenario 3, while viable, is more susceptible to uncertainties. These findings complement the ranking analysis and provide strong quantitative evidence supporting the decision-making process.

The Monte Carlo-TOPSIS analysis (Figure 7) demonstrates remarkable stability in scenario ranking, even under combined uncertainties in weights and system performance. Across all uncertainty levels ($\pm 10\%$ to $\pm 50\%$), Scenario 1 (PV-Grid) consistently achieved the highest closeness-to-ideal index, maintaining its superior performance. Scenario 3 (PV-Wind-Grid) followed as the second-ranked option, with Scenarios 4 (Wind-Grid) and 2 (Grid) consistently ranking third and fourth, respectively. This underscores the robustness of the decision-making process and the resilience of the ranking to variations in weighting and criteria.

However, examining the distribution of the CC within each scenario reveals more nuanced insights. Scenario 1 (PV-Grid) exhibits a highly concentrated CC distribution, clustered closely around 1, with a

mean of approximately 0.985 and a minimal IQR. This signifies exceptional performance stability, even under substantial uncertainty. In contrast, Scenario 3 (PV-Wind-Grid) displays a broader CC distribution, clearly indicating greater sensitivity to changes in weights and criteria, though its performance remains consistently

close to that of Scenario 1. Scenarios 4 (Wind-Grid) and 2 (Grid) exhibit CC distributions reflecting comparatively poor performance, with mean values of approximately 0.14 and 0.036, respectively, positioning them closer to the Negative Ideal Solution (NIS) and further from the ideal.

Table 5. IQR of TOPSIS closeness coefficient for different scenarios under varying uncertainty levels.

Uncertainty Level	Scenario 1 (PV-Grid)	Scenario 2 (Grid)	Scenario 3 (PV-Wind-Grid)	Scenario 4 (Wind-Grid)
$\pm 10\%$	0.00095	0.00291	0.01869	0.00978
$\pm 20\%$	0.00128	0.00410	0.02522	0.01316
$\pm 30\%$	0.00191	0.00621	0.03805	0.01977
$\pm 40\%$	0.00259	0.00844	0.05181	0.02663
$\pm 50\%$	0.00475	0.01419	0.09429	0.04899

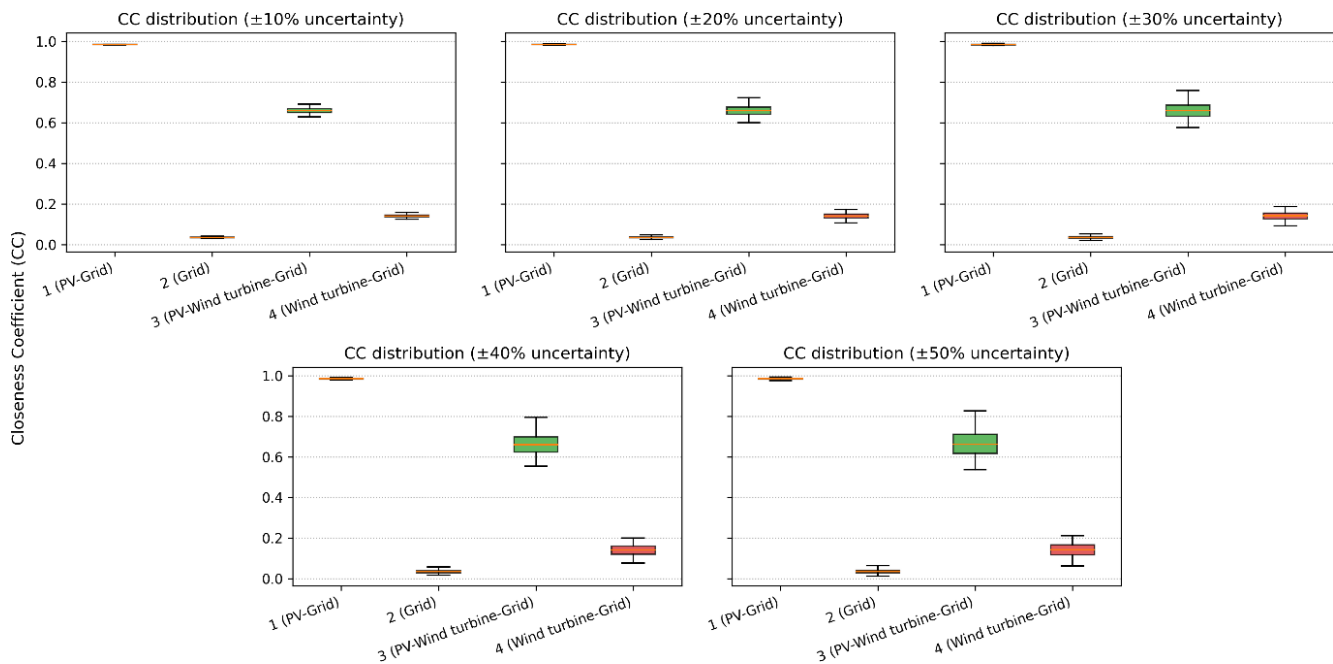


Fig. 7. Box plot of the TOPSIS closeness coefficient distribution for different scenarios under simultaneous uncertainty in criteria weights and performance parameters, using Monte Carlo simulation.

Quantitative analysis confirms these observations. Scenario 1 (PV-Grid) achieves a mean CC of 0.984738 with an IQR of 0.000950, signifying stable performance proximate to the ideal solution. Scenario 3 (PV-Wind-Grid) exhibits a mean CC of 0.659164 and an IQR of 0.018692, indicating heightened sensitivity to uncertainty while maintaining its second-place ranking. Scenario 4 (Wind-Grid) demonstrates a mean CC of 0.140888 and an IQR of 0.009781, reflecting its relative weakness and proximity to the anti-ideal solution. Finally, Scenario 2 (Grid) achieves a mean CC of 0.035519 with an IQR of 0.002905, confirming its position as the

least favorable option and its closeness to the NIS.

Qualitatively, Scenario 1 (PV-Grid) consistently delivers the highest performance due to its superior performance across all cost, emission, and renewable energy criteria compared to the alternatives. This scenario maintains its top ranking across all uncertainty levels. Scenario 3 (PV-Wind-Grid) ranks second, exhibiting slightly lower performance than Scenario 1. Its sensitivity to uncertainty is attributable to the simultaneous utilization of two renewable energy sources (solar and wind). Scenario 4 (Wind-Grid) significantly underperforms, primarily due to its reliance solely on wind

energy and its limited effectiveness in reducing costs and emissions. Scenario 2 (Grid) consistently demonstrates poor performance due to its lack of renewable energy integration and its greater dependence on the electricity grid, resulting in substantially lower scores for CO₂ emissions and cost.

6 Research Limitations

Although the proposed framework presented in this study provides an effective methodology for optimizing the performance of hybrid energy systems, several limitations should be acknowledged to properly contextualize the findings and assess their generalizability. First, with respect to the geographical scope, the analyses conducted in this study are limited to a specific region with unique climatic characteristics and a defined grid connection status. Therefore, extending the findings to other regions would require site specific adjustments and recalibration based on local datasets.

Second, regarding economic parameters and demand characteristics, the economic performance indicators are highly sensitive to local energy tariffs and demand side management policies. In the present study, these parameters were treated as fixed inputs based on the current regulatory framework. However, future extensions of this study could incorporate potential fluctuations in tariff structures and dynamic demand response mechanisms to enhance the adaptability of the model to evolving energy market conditions. Finally, concerning uncertainty modeling, although a deterministic probabilistic hybrid approach was employed to account for variability, simplified uncertainty representations were adopted to preserve computational tractability and ensure model efficiency. While this approach provides a balance between accuracy and computational feasibility, future research may utilize robust optimization or interval optimization methods to capture more complex stochastic variables and improve system resilience under extreme operational conditions.

7 Conclusions

This study addresses the challenge of simultaneously providing electricity, heat, and clean fuel within the building sector, particularly in regions heavily reliant on grid electricity and fossil fuels. A review of the existing literature revealed that many studies are limited in scope and often focus on only a few scenarios. These studies also fail to systematically incorporate economic uncertainties and the inherent variability of renewable resources into the decision-making process. Integrated electricity-heat-hydrogen systems at the household scale remain relatively underexplored.

Consequently, this research was motivated by the need for a comprehensive and robust decision-making framework, grounded in real-world Iranian data, to address technical, economic, and environmental considerations concurrently. The primary innovation of this study lies in integrating detailed system simulation with fuzzy multi-criteria decision-making and Monte Carlo-based uncertainty analysis. This approach enables a rigorous evaluation of scenario ranking stability under diverse weighting policies and parameter variations.

Methodologically, various configurations incorporating PV arrays, WT, batteries, electrolyzers, and grid connections were simulated using HOMER software. The resulting outputs served as inputs for fuzzy TOPSIS analysis. Subsequently, sensitivity and Monte Carlo analyses were employed to assess the impact of uncertainty on scenario rankings. The evaluation criteria encompassed the cost of energy production, hydrogen production cost, CO₂ emissions, the proportion of renewable energy utilized, and overall system performance indicators. The key findings of this research, presented quantitatively, qualitatively, and comparatively, are summarized below:

- The PV-Grid scenario consistently achieved the highest CC to the ideal solution ($CC \approx 0.98-0.99$) under both cost-oriented and climate-oriented weighting policies, establishing it as the optimal option.
- The combined PV-Wind-Grid scenario, while exhibiting favorable performance, ranked second in terms of ranking stability and proximity to the ideal solution ($CC \approx 0.74-0.79$).
- Scenarios with greater dependence on the grid or wind energy alone demonstrated significantly lower CC ($CC \approx 0.02-0.13$) and were deemed less robust from a decision-making perspective.
- Monte Carlo analysis revealed a 99% probability of the PV-Grid scenario achieving the first rank, while other scenarios exhibited negligible probabilities.
- The exceptionally small IQR values and stable average CC within a $\pm 50\%$ parameter variation range confirmed the robustness of the final decision.

In conclusion, the results of this study demonstrate that, under current Iranian conditions, combining solar energy with a grid connection is both economically and environmentally optimal. This configuration also offers a significant advantage in decision-making stability under uncertainty compared to alternative system configurations. These findings provide a practical decision-support tool for energy system designers, researchers, and policymakers in the building sector, facilitating the development of sustainable energy strate-

gies at the household scale.

Future studies should investigate the impact of dynamic variables such as time-varying electricity tariffs, the projected growth in demand for hydrogen vehicles, more detailed modeling of consumer behavior, and the development of dynamic, multi-period decision-making frameworks. Furthermore, extending the analysis to neighborhood and urban scales and comparing the results across different climates within Iran could enhance the generalizability of these findings.

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