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Robust Provincial Prioritization of Hybrid PV–Wind–Fuel Cell Systems in Iran Using TOPSIS and Monte Carlo Robustness Analysis

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Abstract:

The growing demand for energy and the need to reduce emissions have made hybrid renewable energy systems (HRES) a strategic priority. Among these systems, the integration of solar, wind, and fuel cell resources in a complementary structure offers significant potential for reliable and low-emission energy supply. However, optimal site selection for deploying such systems – particularly in countries with diverse climatic and contextual conditions like Iran – presents a multi-criteria challenge accompanied by inherent uncertainty. This study proposes an integrated decision-making framework for prioritizing solar–wind–fuel cell hybrid systems across Iran's 31 provincial capitals. The technical, economic, and environmental performance of the hybrid system was simulated using HOMER, generating indicators such as Cost of Energy (COE), Net Present Cost (NPC), CO2 emissions, renewable energy share, and capacity factors. These indicators, along with contextual criteria like population, natural disaster risk, and land price, were integrated into the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank the provinces. To assess robustness, an uncertainty analysis based on Monte Carlo simulation (10,000 iterations) was conducted. Results indicate that Tehran Province exhibits the highest closeness coefficient (~0.69) with a greater than 90% probability of being ranked among the top five. Conversely, regions such as Kerman and Sistan and Baluchistan consistently obtained lower ranks across most scenarios. This study demonstrates that integrating TOPSIS with Monte Carlo simulation provides not only quantitative rankings but also a risk-informed decision-making tool, effectively supporting policymakers in the siting of pilot renewable energy projects at the national scale.

Keywords:

Multi-criteria decision-making, Uncertainty analysis, Spatial prioritization, Cost of energy, System sustainability

1. Introduction

The global transition from fossil-fuel-based energy systems to low-carbon and sustainable alternatives has emerged as a critical strategy for mitigating climate change and enhancing energy security [1]. Reliance on fossil resources has not only increased greenhouse gas emissions but has also heightened energy systems' vulnerability to fuel price volatility and geopolitical risks [2]. In this context, renewable energy sources—particularly solar and wind—are pivotal in energy transition scenarios due to their widespread availability and minimal environmental impact [3].

Despite the inherent advantages of solar and wind energy, their intermittency and dependence on climatic conditions present challenges to stable and reliable energy supply [4]. Studies consistently demonstrate that relying on a single renewable source—especially at local or regional scales—is insufficient to meet continuous energy demand [5]. Consequently, HRES, combining multiple energy sources and storage, have gained prominence as a viable solution [6].

Among various HRES configurations, the PV–Wind–Fuel Cell combination is particularly promising due to its complementary generation profiles and the ability to store energy as hydrogen [7]. The fuel cell, as a clean and controllable power-generation unit, mitigates fluctuations in solar and wind output, thereby enhancing system stability [8]. Previous research indicates that integrating fuel cells into hybrid systems can simultaneously reduce energy costs and CO_2 emissions [9].

Designing and evaluating HRES performance requires a simultaneous analysis of technical, economic, and environmental indicators [10]. Advanced simulation tools, such as HOMER, are widely used for modeling, optimizing, and comparing different HRES configurations [11]. HOMER facilitates quantitative assessment of key indicators, including COE, NPC, renewable energy share, and emissions levels [12].

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However, simulation results alone are insufficient for optimal decision-making, as selections are typically influenced by a heterogeneous set of often-conflicting criteria [13]. Consequently, energy planning increasingly uses Multi-Criteria Decision Making (MCDM) [14] to integrate simulation data with broader factors like population, natural disaster risk, and land costs [15].

The TOPSIS is a widely adopted MCDM technique for evaluating renewable energy systems, owing to its simplicity, mathematical transparency, and interpretability [16]. TOPSIS selects the alternative closest to the positive ideal solution and farthest from the negative ideal solution [17]. Numerous studies have demonstrated TOPSIS's effectiveness in spatially and scenario-based ranking hybrid energy systems at regional and national scales [18].

A key limitation of MCDM-based approaches is their sensitivity to data uncertainty and parameter fluctuations [19]. To mitigate this, Monte Carlo simulation can also be employed to assess the robustness of ranking results [20]. By generating thousands of random scenarios, Monte Carlo simulation allows for evaluating ranking stability and assessing decision-making risk [21].

This paper introduces an integrated, risk-based decision-making framework for spatially prioritizing PV–Wind–Fuel Cell hybrid systems across Iran's provinces. The framework integrates precise system simulation results from HOMER with the MCDM method TOPSIS and uncertainty analysis based on Monte Carlo simulation. Economic indicators (COE and NPC), environmental indicators (CO_2 emissions), operational indicators (renewable energy share and capacity factors), and contextual criteria (population, natural disaster risk, and land price) are evaluated cohesively. The innovation of this research lies in moving beyond deterministic ranking to a statistical evaluation of rank stability, enabling sensitivity assessment, identifying low-risk alternatives, and differentiating marginal options. Moreover, the study provides not only provincial rankings but also a robust analytical tool for policymakers, identifying pilot regions, and guiding national-scale planning of HRES.

2. Study Area

This research analyzes 31 provincial capitals of Iran, representing each province and playing a central role in the country's energy consumption, population distribution, economic infrastructure, and developmental decision-making [22]. Selecting provincial centers as reference points aligns results with provincial policies and national strategic planning, ensuring broad generalizability and practical applicability [23]. These cities generally exhibit the highest population density and the greatest concentration of industrial and service-sector activities within their respective provinces. Therefore, they were selected as representative locations for evaluating the deployment feasibility and relative performance of hybrid renewable energy systems across the provinces [24].

The selection of these sites also reflects the country's climatic, geographical, and economic diversity, encompassing a range of conditions—from hot, arid regions to semi-arid, temperate, and cold areas [25]. This variability creates distinct solar and wind potentials, energy consumption patterns, and HRES performance, facilitating a multidimensional comparison [26]. Furthermore, the geographical distribution of provincial centers varies in terms of environmental and natural hazards, a critical consideration for long-term energy infrastructure deployment [27].

Tables 1 and 2 compile quantitative and contextual data for each provincial capital, including geographical coordinates, elevation, demographic indicators, land prices, natural hazard risk, average wind speed, atmospheric clearness index, and average annual solar irradiation. These data serve as key inputs for the multi-criteria decision analysis and are essential for interpreting HRES simulation results and the final spatial ranking. The population index was considered a benefit criterion because it was not intended to directly represent actual electricity consumption; rather, it was used as a proxy for potential energy demand, system scalability, infrastructure development capacity, and the socio-economic impact of renewable energy investments. Consequently, provinces with larger populations and favorable renewable energy resources can potentially benefit from greater economies of scale, wider consumer coverage, and higher overall investment effectiveness. Therefore, a higher population value was regarded as a desirable attribute in the decision-making process [28]. Land price represents an indirect cost component crucial for economic assessment [29]. Elevation can indirectly influence temperature patterns, air density, and the performance of wind and solar systems [30]; average wind speed is critical for estimating power output from wind turbines [31]. Similarly, the clearness index and annual solar irradiation provide insights into solar resource quality and PV system efficiency [32]. The natural hazard risk index assesses infrastructure vulnerability, integrating safety, resilience, and sustainability into decision-making [33].

The significance of the data presented in Table 1 is amplified when integrated with the technical and economic indicators derived from hybrid system simulations. Combining spatial contextual data with energy simulation outputs enables a shift from a purely technical analysis toward a comprehensive and realistic evaluation that addresses the practical needs of policymakers and energy planners [36]. This approach identifies locations that seem favorable based solely on resource potential but are unsuitable when socio-economic or risk factors are considered.

Overall, selecting provincial capitals as study sites and employing a unified dataset encompassing both technical and contextual variables establishes a foundation for results that are scientifically sound and practically relevant. These findings can guide pilot site selection, investment prioritization, and HRES development strategies at provincial and national levels.

Table 1. Demographic and contextual data by province (Iran)

Province	City	Population [33]	Natural disasters (%) [34]	Land price (k$/m^2) [33]
Markazi	Arak	520944	4	2.06
Ardabil	Ardabil	529374	8	1.54
Khuzestan	Ahvaz	1205000	15	1.67
Hormozgan	Bandarabbas	526648	19	1.8
South Khorasan	Birjand	203636	11	0.789
North Khorasan	Bojnord	228931	10	1.15
Bushehr	Bushehr	223504	9	1.27
Isfahan	Isfahan	1961260	28	2.56
Golestan	Gorgan	350676	18	1.44
Hamedan	Hamedan	554406	6	2.09
Ilam	Ilam	194030	9	0.917
Alborz	Karaj	1592492	2	2.65
Kerman	Kerman	537718	28	0.746
Kermanshah	Kermanshah	946651	10	1.98
Lorestan	Khorramabad	373416	19	0.864
Razavi Khorasan	Mashhad	3001184	7	2.36
West Azerbaijan	Urmia	1558693	7	1.4
Qazvin	Qazvin	402748	7	1.84
Qom	Qom	1084125	4	3.16

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Gilan	Rasht	679995	23	1.84
Kordistan	Sanandaj	412767	4	1.71
Mazandaran	Sari	347102	13	1.98
Semnan	Semnan	185129	8	1.39
Chaharmahal and Bakhtiari	Shahrekord	190441	8	1.16
Fars	Shiraz	1565572	17	1.99
East Azerbaijan	Tabriz	736224	21	2.33
Tehran	Tehran	8693706	16	6.79
Kohgiluyeh and Boyer-Ahmad	Yasuj	134532	6	0.364
Yazd	Yazd	529673	4	1.06
Sistan and Baluchistan	Zahedan	587730	23	0.924
Zanjan	Zanjan	430871	7	2.01

Table 2. Climatic and geographical factors for renewable energy assessment in Iranian provinces [33]

Province	**City**	**Latitude [35]**	**Longitude [35]**	**Average annual radiation (kWh/m^2-day) [35]**	**Clearness index (-)**	**Average wind speed (m/s) [35]**	**Elevation from sea level (m) [35]**
Markazi	Arak	34.1	49.8	5.04	0.599	1.45	1708
Ardabil	Ardabil	39.7	47.9	4.01	0.505	5.98	327
Khuzestan	Ahvaz	31.3	48.7	5.13	0.592	2.52	22
Hormozgan	Bandarabbas	27.2	56.4	5.4	0.602	6.01	10
South Khorasan	Birjand	32.9	59.2	5.31	0.620	5.57	1491
North Khorasan	Bojnord	37.5	57.3	4.61	0.567	4.71	1511
Bushehr	Bushehr	28.9	50.8	5.96	0.670	4.76	0
Isfahan	Isfahan	32.5	51.7	5.34	0.622	4.70	1550
Golestan	Gorgan	36.8	54.5	4.35	0.530	3.78	1364
Hamedan	Hamedan	34.9	48.5	5.05	0.601	2.03	1749
Ilam	Ilam	33.6	46.4	5.05	0.596	4.01	1101
Alborz	Karaj	35.8	51.0	4.9	0.590	5.10	1328
Kerman	Kerman	30.3	57.0	5.34	0.611	2.66	1754
Kermanshah	Kermanshah	34.3	47.1	5.08	0.605	4.77	1322
Lorestan	Khorramabad	33.5	51.4	5.17	0.609	4.20	1810
Razavi Khorasan	Mashhad	36.3	59.6	4.67	0.568	3.50	999
West Azerbaijan	Urmia	37.5	45.1	4.87	0.600	1.89	1316
Qazvin	Qazvin	36.3	49.2	4.56	0.544	5.3	1422
Qom	Qom	34.7	51.0	5.01	0.597	5.17	1546
Gilan	Rasht	37.2	50.2	4.13	0.508	5.27	11
Kurdistan	Sanandaj	35.3	47.0	4.96	0.597	4.87	1899
Mazandaran	Sari	36.6	53.1	3.99	0.485	3.81	822
Semnan	Semnan	35.6	53.4	4.79	0.576	4.03	1451
Chaharmahal and Bakhtiari	Shahrekord	32.3	50.9	5.06	0.590	4.25	2430
Fars	Shiraz	29.5	52.5	5.49	0.622	4.84	1481
East Azerbaijan	Tabriz	38.1	46.3	4.59	0.571	6.10	1361
Tehran	Tehran	35.7	51.3	4.9	0.589	5.26	1191
Kohgiluyeh and Boyer-Ahmad	Yasuj	30.8	51.7	5.38	0.616	4.28	1940
Yazd	Yazd	31.9	54.4	5.41	0.625	5.19	1230
Sistan and Baluchistan	Zahedan	29.5	60.9	5.42	0.615	3.29	1370
Zanjan	Zanjan	36.7	48.5	4.75	0.578	2.83	1663

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Fig. 1 illustrates the spatial distribution of renewable energy potentials—including solar, wind, hydropower, expansion turbine, and biomass—across Iran's provinces, providing a comprehensive depiction of the country's heterogeneous energy resources [37]. The figure demonstrates that Iran possesses a diverse, multi-source renewable energy potential, where no single resource dominates all regions; rather, each province exhibits a unique combination of energy capabilities. This characteristic underscores the necessity of spatially analyzing hybrid energy systems.

As shown in Fig. 1, central and southern provinces such as Yazd, Kerman, Isfahan, and Markazi exhibit exceptionally high solar energy potential, making them prime candidates for PV system development. Wind energy potential is heterogeneous yet substantial across the country; for example, Qazvin Province, with a value of approximately 164.7, is identified as having the highest wind potential nationwide, while Sistan and Baluchistan and parts of Razavi Khorasan also demonstrate favorable wind resources. Furthermore, East Azerbaijan and Gilan provinces exhibit promising wind potential due to their topographical and regional wind conditions, highlighting their roles as complementary components within hybrid energy systems.

Northern and northwestern provinces—particularly Gilan, Mazandaran, Ardabil, Kurdistan, Markazi, and Tehran—have relatively higher shares of hydropower and biomass potential, primarily due to their hydrological features and water resource availability. Additionally, the potential for expansion turbines observed in provinces such as Isfahan and Khuzestan indicates the presence of underexplored yet valuable opportunities for harnessing energy from gas pressure drops and industrial processes—resources that can serve as beneficial complements in hybrid system configurations.

The importance of this figure within the present research lies in its clear demonstration that no single province is ideally positioned across all renewable resource categories and that relying solely on a single renewable source is neither sustainable nor optimal for energy supply. This spatial heterogeneity provides a logical basis for selecting provincial capitals as focal study areas and reinforces the necessity of employing solar–wind–fuel cell hybrid structures. Moreover, Fig. 1 helps explain variations observed in simulation outcomes and provincial rankings—particularly cases where provinces with high potential for one specific resource fail to achieve high overall ranks due to deficiencies in other resources or contextual constraints.

In summary, Fig. 1 serves as a key informational layer within the study area section, establishing a clear connection among intrinsic renewable resource potentials, the chosen hybrid energy system structure, and the results of the multi-criteria decision analysis. Using this figure alongside the quantitative data compiled in Table 1 facilitates a comprehensive, realistic, and spatially grounded analysis, providing a robust foundation for subsequent simulation and ranking stages.

Fig. 1. Renewable energy capacity for electricity generation in the provinces of Iran [37]

3. Methodology

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Fig. 2 illustrates the overall framework of the present research methodology, encompassing the collection of spatial and climatic data for Iran, hybrid system simulation using HOMER software, multi-criteria ranking via the TOPSIS method, and uncertainty analysis through Monte Carlo simulation. This integrated structure elucidates the logical connection between input data, techno-economic–environmental assessment, and the final prioritization of provinces.

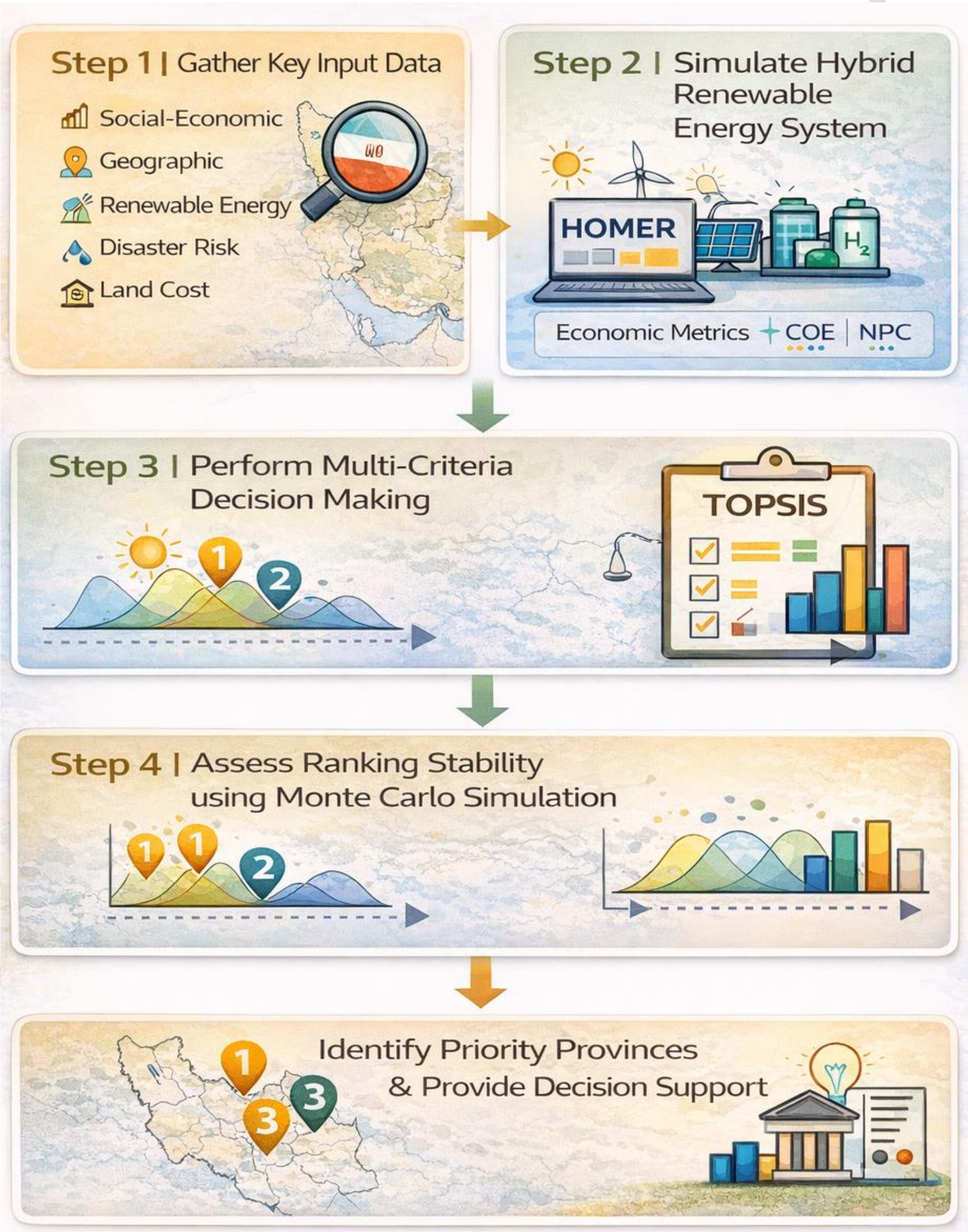

Fig. 2. Integrated framework for assessing and spatially prioritizing a solar–wind–fuel cell hybrid system based on HOMER simulation, the TOPSIS method, and Monte Carlo uncertainty analysis

In this study, HOMER software was utilized to perform simultaneous technical, economic, and environmental analyses [38, 39]. The software is capable of simulating both electricity and hydrogen production systems in grid-connected and standalone modes [40, 41]. Optimization within HOMER is based on minimizing the total NPC, and system performance is simulated over a one-year period using short time steps [42, 43].

It should be noted that the hybrid system capacity used in this study was considered solely as a standard reference system for comparing the provinces. The objective of the study was not to design energy systems at the provincial scale or to estimate the actual electricity demand of each province, but rather to evaluate and compare the relative technical, economic, and environmental performance of different provinces under identical conditions. Therefore, all provinces were simulated in HOMER using the same installed capacity and identical economic assumptions. Consequently, indicators such as COE and NPC were employed as comparative metrics for ranking alternatives and should not be interpreted as absolute values representing the total energy consumption or actual energy requirements of each province.

By inputting monthly average solar radiation data, HOMER software calculates the Clearness Index using the following equation [44]:

$$k_t = \frac{H_{ave}}{H_{o,ave}} \tag{1}$$

where H_{ave} is the amount of radiation received on the ground surface, and $H_{o,ave}$ is the extraterrestrial solar radiation.

The power generated by solar panels in HOMER is calculated as [45]:

$$P_{PV} = Y_{PV} f_{PV} \frac{\overline{G_T}}{G_{T,STC}} \tag{2}$$

In this equation, Y_{PV} is the nominal output power of the solar panel under standard conditions (kW), f_{PV} is the power derating factor, $\overline{G_T}$ is the solar radiation reaching the collector surface (kW/m²),

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andis the radiation under standard conditions (1 kW/m²). The tilt angle of the solar panels is $\overline{G_{T,STC}}$ considered equal to the latitude of the study location [46].

The power output of a wind turbine in real conditions depends on its installation site and, particularly, its altitude above sea level [47, 48]. In HOMER software, the power generated by the wind turbine is obtained from the following equation [49]:

$$P_{WTG} = \frac{\rho}{\rho_0} P_{WTG,\,STP} \tag{3}$$

where ρ is the air density under actual conditions, ρ_0 is the air density under standard conditions, and $P_{WTG,\,STP}$ is the nominal power of the turbine, which is extracted from the turbine's power curve.

The efficiency of the fuel cell/diesel generator was calculated using the following equation [50]:

$$\eta = \frac{3.6P}{\dot{m}_{fuel}\, LHV_{fuel}} \tag{4}$$

In this equation, P represents the total annual electrical energy generated (kWh/year), $\dot{m}_{fuel}$ is the annual fuel consumption (kg/year), and LHV_{fuel} is the lower heating value of the fuel (MJ/kg). HOMER calculates the required number of batteries for each operating condition using [51]:

$$N_{Batteries} = \frac{E_d \times n_d}{V_{battery} \times AH \times DOD} \tag{5}$$

In Eq. (5), E_d represents the system daily energy consumption, n_d is the number of days for which backup power supply is necessary, $V_{battery}$ is the nominal voltage of the battery, AH is the battery capacity in ampere-hours, and DOD represents the allowable depth of discharge for the battery.

The main output of HOMER software is a list of proposed systems ordered by the total *NPC*. This index is calculated using the following equation [52]:

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$$NPC = \frac{C_{ann,total}}{CRF(i, R_{proj})} \tag{6}$$

where $C_{ann,total}$ is the total annual cost (USD), CRF is the capital recovery factor, i is the real interest rate, and R_{proj} is the project's lifetime. The capital recovery factor, which indicates capital recovery over N years, is obtained from the following equations [53]:

$$CRF = \frac{i(1+i)^N}{(1+i)^N - 1} \tag{7}$$

$$i = \frac{i' - f}{1+f} \tag{8}$$

Finally, the COE produced during the project's operational period is calculated as [54]:

$$COE = \frac{C_{ann,total}}{E_{load\ served}} \tag{9}$$

where $E_{load\ served}$ is the actual amount of electrical energy supplied by the hybrid system throughout a year (kWh/year), priced in USD.

In this research, to rank the 31 provincial capitals of Iran based on their suitability for implementing a solar–wind–fuel cell hybrid system, an MCDM framework based on the TOPSIS method was employed. The input data were extracted from three main sources: (1) contextual and environmental indicators including population, natural disaster risk, and land price for each province; (2) economic and environmental indicators resulting from the hybrid system simulation in HOMER software, including the COE, total NPC, and CO_2 emissions; and (3) energy performance indicators including the renewable fraction (Renewable Fraction), wind turbine capacity factor, PV capacity factor, and annual fuel cell production. This combination of data allows for the simultaneous evaluation of economic, environmental, performance, and contextual dimensions. In the first step, a decision matrix $X=[x_{ij}]$ was formed, where each row i represents a province (i = 1, …, 31) and each column j represents a decision criterion (j = 1, …, 10). The selected criteria included COE, NPC, CO_2, renewable fraction, wind capacity factor, solar capacity factor, fuel cell production, population, natural disaster risk, and land price. Subsequently, the nature of each criterion was determined; criteria such as COE, NPC, CO_2, natural disaster risk, and land price were considered cost criteria (Cost), while criteria such as renewable fraction, capacity factors, fuel cell production, and population were considered benefit criteria (Benefit).

To eliminate the effect of different units and scale the data, the decision matrix was normalized using the standard vector normalization of TOPSIS. Normalization of each element was performed according to the following equation [55]:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \tag{10}$$

where r_{ij} is the normalized value of criterion j for option i. The output of this stage was the normalized matrix $R=[r_{ij}]$, which served as the basis for applying weights.

In the next step, the weight of each criterion was determined to reflect its relative importance in decision-making. The weights were defined such that their sum equals one ($\sum w_j=1$), establishing a suitable balance among the economic, environmental, energy performance, and contextual criteria [56]. To determine the relative importance of the evaluation criteria in the TOPSIS method, a hierarchical weighting approach based on engineering judgment and the relative significance of the criteria in hybrid energy system assessment was employed. The considered criteria were classified into three main groups, namely economic–environmental criteria, energy performance criteria, and contextual–implementation criteria. Since the objective of this study is to evaluate the performance and feasibility of deploying solar–wind–fuel cell hybrid energy systems in the provincial capitals of Iran, the economic–environmental and energy performance groups were considered the most influential decision-making dimensions and were each assigned 40% of the total weight. The remaining 20% of the total weight was allocated to contextual criteria. Within the economic–environmental group, COE, NPC, and CO_2 emissions were assigned weights of 0.18, 0.12, and 0.10, respectively. Within the energy performance group, Renewable Fraction, Wind Capacity Factor, PV

Capacity Factor, and Fuel Cell Production received weights of 0.15, 0.10, 0.08, and 0.07, respectively. Within the contextual group, Population, Natural Disaster Risk, and Land Price were assigned weights of 0.08, 0.07, and 0.05, respectively. The sum of all criterion weights is equal to one.

Accordingly, the final weights were assigned to the criteria, and then the normalized matrix was multiplied by the weight vector to obtain the weighted normalized matrix $V=[v_{ij}]$ as follows [57]:

$$v_{ij} = r_{ij} \times w_j \tag{11}$$

Subsequently, based on the TOPSIS logic, the positive ideal solution A^+ and the negative ideal solution A^- were determined. For benefit criteria, the positive ideal value was set as the maximum and the negative ideal value as the minimum of the weighted values among the options, while for cost criteria, this definition was applied inversely. Mathematically [58]:

$$\begin{aligned} A^+ &= \{v_1^+, v_2^+, \ldots, v_n^+\} \\ A^- &= \{v_1^-, v_2^-, \ldots, v_n^-\} \end{aligned} \tag{12}$$

Then, the distance of each option to the positive and negative ideal solutions was calculated using Euclidean distance [59]:

$$D_i^{\pm} = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^{\pm})^2} \tag{13}$$

Finally, the closeness coefficient (CC) for each province was calculated as the TOPSIS index [60]:

$$CC_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{14}$$

The value of which ranges between zero and one, and the higher it is, the closer the option is to the positive ideal solution and farther from the negative ideal solution. The provinces were then sorted and ranked in descending order based on their CC_i values.

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To evaluate the stability of the TOPSIS ranking against data uncertainty, an uncertainty analysis based on Monte Carlo simulation was performed. First, for each province i, the base value of the TOPSIS closeness coefficient, obtained from the deterministic ranking, was denoted by CC_i. It was then assumed that the actual value of this index could vary within ±20% around the base value due to data uncertainty and parameter fluctuations. Accordingly, in each Monte Carlo iteration k k (with k=1,…, and N = 10,000), a random value for the CC of each province was generated. In this study, the ±20% variation range was adopted as a conservative perturbation scenario for evaluating the robustness and stability of the deterministic TOPSIS ranking. This range should not be interpreted as an uncertainty interval derived from experimental data or the historical variability of climatic and economic variables; rather, it was deliberately selected to represent a relatively broad yet realistic range of potential variations in the final decision-making indicator, thereby enabling the assessment of ranking robustness against relatively significant perturbations while avoiding unrealistic distortions of the decision space. The adoption of such conservative perturbation scenarios is a common and well-established practice in sensitivity and uncertainty analysis, particularly when reliable probability distributions or sufficient experimental data for the input variables are unavailable [61, 62].

Therefore, the obtained results should be interpreted primarily as a ranking robustness analysis rather than a comprehensive uncertainty propagation analysis. Random generation was performed based on a uniform distribution in the range [0.8 CC_i, 1.2 CC_i] [63]:

$$CC_i^{(k)} \sim U\left(0.8CC_i, 1.2CC_i\right) \tag{15}$$

Thus, a simulation matrix of size N×m was formed, where m=31 is the number of provinces, and its components represent $CC_i^{(k)}$ in each iteration. In each iteration, the provinces were re-ranked by sorting the vector $\left\{CC_i^{(k)}\right\}_{i=1}^{m}$ in descending order; rank 1 was assigned to the largest value and rank m to the smallest value. If the rank of province i in iteration k is denoted by $r_i^{(k)}$, then the set $\left\{r_i^{(k)}\right\}_{k=1}^{N}$ constitutes the empirical distribution of the rank for province i.

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Based on this empirical distribution, key statistical indicators were extracted for each province. The mean rank was calculated as the central index of rank stability as follows [64]:

$$\mu_{r,i} = \frac{1}{N}\sum_{k=1}^{N} r_i^{(k)} \tag{16}$$

Also, the standard deviation of rank was calculated as an index of rank dispersion and volatility [65]:

$$\sigma_{r,i} = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(r_i^{(k)} - \mu_{r,i}\right)^2} \tag{17}$$

To assess the probability of each province being in the top groups, the probabilities of being in the top 5 and top 10 ranks were also calculated. These probabilities were obtained by the ratio of the occurrences of the respective event to the total number of iterations [66]:

$$\begin{aligned} P_i\left(Top-5\right) &= \frac{1}{N}\sum_{k=1}^{N} I\,(r_i^{(k)} \le 5) \\ P_i\left(Top-10\right) &= \frac{1}{N}\sum_{k=1}^{N} I\,(r_i^{(k)} \le 10) \end{aligned} \tag{18}$$

where I (.) is the indicator function, which takes a value of 1 if the condition is met and 0 otherwise. After calculating $\mu_{r,i}$, $\sigma_{r,i}$, $P_i\left(Top-5\right)$, and $P_i\left(Top-10\right)$, three plots were generated to visually display the uncertainty analysis results: (1) a plot of the mean rank with standard deviation error bars, (2) a bar chart of the probabilities of being in the *Top*-5 and *Top*-10, and (3) a boxplot of the rank distribution for the top provinces. To draw the boxplot of rank distribution for the top provinces, the rank data $\left\{r_i^{(k)}\right\}$ for a selected number of provinces (in this study, the top 15 provinces based on the lowest $\mu_{r,i}$) were extracted, and distribution statistics including the first quartile Q_1, median Q_2, and third quartile Q_3 were used. The interquartile range was defined as $IQR = Q_3 - Q_1$, and the boxplot display was based on the range [Q_1, Q_3] and the median [67]; thus, the degree of concentration/dispersion of ranks under uncertainty scenarios was clearly observable.

It should be noted that the Monte Carlo analysis conducted in this study was intended to evaluate the relative stability of the TOPSIS ranking against data fluctuations. Within this framework, random perturbations were independently applied to the TOPSIS closeness coefficient within a ±20% range. Therefore, potential dependencies and correlations among variables were not explicitly incorporated into the model. Consequently, the presented results should be interpreted as a robustness analysis of the ranking outcomes rather than as a comprehensive uncertainty analysis of the entire energy system.

To quantitatively characterize the uncertainty associated with the ranking results, the empirical ranking distribution of each province was extracted after performing 10,000 Monte Carlo simulation iterations. Let $r_i^{(k)}$ denote the ranking of province i in the k-th simulation. The 95% confidence interval of the ranking for each province was calculated using the percentile method, as follows:

$$CI_{95\%,i} = \left[Q_{2.5}(r_i^{(k)}), Q_{97.5}(r_i^{(k)}) \right] \tag{19}$$

where $Q_{2.5}$ and $Q_{97.5}$ denote the 2.5th and 97.5th percentiles, respectively, of the empirical ranking distribution obtained from the Monte Carlo simulations. Since ranking is an ordinal and discrete variable, the lower and upper confidence limits were reported as integer ranking values. In addition to the confidence intervals, the mean ranking, ranking standard deviation, and the probability of each province being ranked among the top five and top ten alternatives were also calculated to quantitatively evaluate the robustness and reliability of the ranking results.

Overall, the uncertainty analysis presented in this study should be interpreted as a robustness assessment of the provincial ranking results rather than a complete uncertainty propagation analysis of the hybrid energy system [68, 69]. While this approach is appropriate for evaluating ranking stability under data fluctuations, future studies may extend the proposed framework by propagating uncertainties from the primary input variables throughout the HOMER simulation and multi-criteria decision-making process.

4. Required Data

Since all provinces were evaluated using the same reference hybrid system configuration and a common benchmark load profile, the differences observed in indicators such as COE, NPC, pollutant emissions, and Renewable Fraction primarily reflect differences in renewable energy resource availability and climatic conditions among the provinces rather than differences in actual electricity demand or energy consumption at the provincial scale.

To implement the PV system, input data including monthly average solar radiation intensity (Table 2), the geographical coordinates of the study location (Table 2), and its time zone (GMT+03:30) are necessary. For wind turbines, information regarding average wind speed (Table 2) and installation height above ground level was utilized. Furthermore, other data required for the simulation, such as equipment prices, the lifetime of system components, and the available quantity of each item, are presented in Table 3. It should be noted that the configuration investigated in this study is an off-grid hybrid energy system. No connection to the utility grid was defined in the HOMER model, and the electrical load is supplied solely through wind and solar resources, battery storage, the backup generator, and the hydrogen subsystem.

In this study, a specific set of technical and economic data served as simulation inputs. The annual interest rate was set at 18% [73], the project's lifetime at 25 years [74], the price of each liter of diesel fuel at \$0.011 [75], the diesel generator efficiency at 32%, and the pollutant emission penalty at zero [76]. The amounts of CO, unburned hydrocarbons, suspended solids, and NO_x present in diesel fuel were considered to be 6.5, 0.72, 0.49, and 58 g/L, respectively [77]. The electrical power demand profile is presented in Fig. 3. Based on this profile, the average and maximum daily electrical energy demand are 19.4 kWh and 2.91 kW, respectively.

The load profile presented in Fig. 3 represents a benchmark load profile that was uniformly applied to all provinces. This profile was adopted to provide a common basis for comparing renewable energy resource potential and hybrid system performance across different provinces and does not represent the actual electricity consumption or energy demand at the provincial scale.

Table 3. The system information

Component	Capacity (kW)	Capital price ($)	Replacement price ($)	Operating& maintenance cost ($/year)	Lifetime (year)	Efficiency (%)	Schematic

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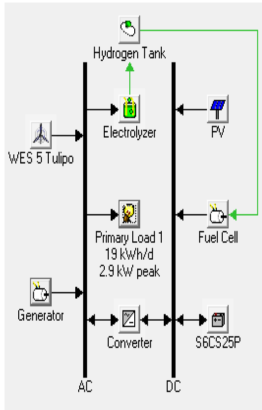
PV [34]	1	7000	1389	20	20	80
Wind turbine [70]	1	5000	5000	75	20	-
Diesel generator [71]	1	375	375	0.05	15000 hours	30
Electrolyzer [34]	1	2000	1500	25	20	75
H_2 tank [34]	1	1300	1200	15	20	-
Fuel cell [34]	1	3000	2500	0.175	43800 hours	25
Converter [34]	1	800	750	8	15	95
Battery [72]	1	1200	1200	10	-	-



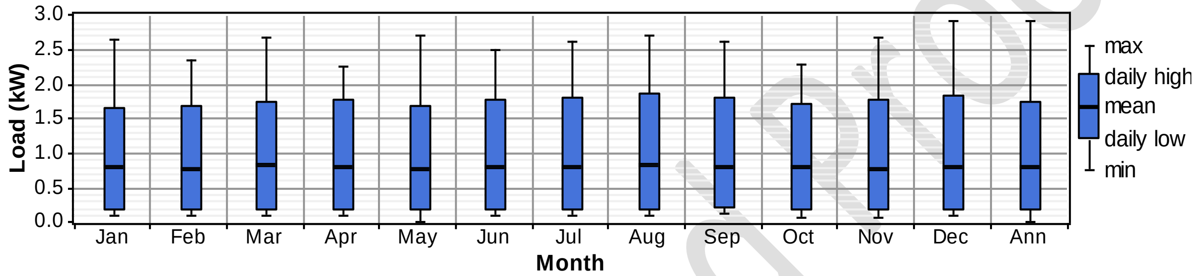


Fig. 3. Seasonal electricity profile

5. Results and discussions

The economic and environmental evaluation results presented in Table 4 reveal significant differences in the performance of the hybrid solar-wind-fuel cell system across various provinces. These differences, observed in terms of the COE, total NPC, and CO_2 emissions, are rooted in climatic conditions, the energy source mix, and the system's reliance on renewable resources. The COE in the studied provinces varies within a relatively narrow range, from approximately \$0.641/kWh in Bandarabbas (Hormozgan) to about \$0.723/kWh in Arak (Markazi). This variation directly indicates the influence of renewable resource potential and the proportion of clean energy on the final energy production cost. Provinces such as Hormozgan, Ardabil, Gilan, East Azerbaijan, and Tehran demonstrate more favorable economic performance compared to the national average, with COE values below \$0.66/kWh. Conversely, provinces like Markazi, Hamadan, West Azerbaijan, and Zanjan face higher COE values due to a lower share of renewable energy and greater dependence on backup components.

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A similar trend is observed in NPC values, with the lowest total system lifecycle cost recorded for Hormozgan province (approximately $24,679), followed by Ardabil and Gilan. The highest NPC values, however, are reported in provinces such as Markazi, Hamadan, and West Azerbaijan. This direct correlation between COE and NPC suggests that provinces with stronger renewable energy resources are not only more cost-effective in terms of energy production but also present more economically viable options for long-term investment. From an environmental perspective, CO_2 emissions range from approximately 4334 kg/year in Bandarabbas to over 8100 kg/year in Arak. These findings highlight considerable differences in the utilization of clean resources and the reduction of dependence on fossil fuels across different provinces.

The energy assessment results presented in Table 5 provide a more detailed view of the system's operational structure, demonstrating that the climatic and environmental disparities observed in Table 2 are directly linked to energy production indices and resource capacity factors. Specifically, provinces like Ardabil, Bandarabbas, Rasht, Tabriz, Yazd, and Tehran exhibit high wind turbine capacity factors (over 35%), leading to substantial annual wind energy production. This, in turn, increases the renewable fraction to over 70% in these regions. In contrast, provinces such as Arak, Hamadan, Urmia, and Zanjan have very low wind capacity factors (less than 5%) and limited wind energy production, resulting in lower renewable fractions (around 22–38%) and consequently higher costs and pollutant emissions.

Regarding solar energy, PV system capacity factors remain relatively stable across most provinces (around 15–21%). However, provinces like Yazd, Fars, Bushehr, and Bandarabbas, due to higher solar irradiation, register greater annual solar energy production, which plays a significant role in improving the overall system performance. Fuel cell energy production contributes a relatively limited portion to the total production in all provinces (with capacity factors less than 2%). Nevertheless, its role as a reliable backup source is crucial for ensuring energy supply stability and mitigating fluctuations in renewable energy generation. Furthermore, converter loss values indicate that provinces with a higher share of wind and solar energy generally experience lower losses in the

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energy conversion chain, contributing to improved overall system efficiency. In summary, the most significant quantitative, qualitative, and comparative findings from Tables 4 and 5 can be consolidated as follows:

- Provinces with a renewable energy share exceeding 70% (e.g., Ardabil, Bandarabbas, Rasht, Tabriz, Yazd, Tehran, Bushehr, and Qazvin) exhibit the lowest COE, NPC, and CO_2 emissions.
- Provinces with low wind capacity factors (such as Arak, Hamadan, and Urmia), even with favorable solar energy output, demonstrate weaker economic and environmental performance.
- The relatively narrow differences in COE among provinces suggest that the energy source mix structure, rather than the absolute magnitude of production, is the primary determinant of the system's economic performance.
- The fuel cell primarily operates as a backup and long-term energy storage component and contributes to improving the operational flexibility of the system during periods of reduced renewable energy generation.
- Comparative results confirm that provinces with a balanced mix of wind and solar energy offer more stable and cost-effective performance than single-source provinces.

Table 4. Results of economic and environmental assessment

Province	City	COE ($/kWh)	Total NPC ($)	CO_2 (kg/Year)
Markazi	Arak	0.723	27850	8105
Ardabil	Ardabil	0.647	24918	4576
Khuzestan	Ahvaz	0.709	27297	7398
Hormozgan	Bandarabbas	0.641	24679	4334
South Khorasan	Birjand	0.657	25297	4994
North Khorasan	Bojnord	0.672	25873	5657
Bushehr	Bushehr	0.659	25395	5144
Isfahan	Isfahan	0.668	25744	5522
Golestan	Gorgan	0.689	26553	6448
Hamedan	Hamedan	0.717	27632	7824
Ilam	Ilam	0.680	26192	6052
Alborz	Karaj	0.663	25546	5292
Kerman	Kerman	0.710	27348	7412
Kermanshah	Kermanshah	0.667	25689	5472
Lorestan	Khorramabad	0.679	26144	5986

Razavi Khorasan	Mashhad	0.695	26755	6683
West Azerbaijan	Urmia	0.718	27665	7890
Qazvin	Qazvin	0.661	25468	5199
Qom	Qom	0.663	25516	5257
Gilan	Rasht	0.656	25271	4972
Kordistan	Sanandaj	0.669	25783	5550
Mazandaran	Sari	0.689	26525	6408
Semnan	Semnan	0.683	26286	6153
Chaharmahal and Bakhtiari	Shahrekord	0.681	26231	6080
Fars	Shiraz	0.667	25678	5438
East Azerbaijan	Tabriz	0.652	25107	4756
Tehran	Tehran	0.660	25407	5130
Kohgiluyeh and Boyer-Ahmad	Yasuj	0.677	26075	5906
Yazd	Yazd	0.659	25394	5121
Sistan and Baluchistan	Zahedan	0.698	26869	6825
Zanjan	Zanjan	0.707	27226	7294

Table 5. Energy assessment results

Province	City	Renewable fraction (%)	PV production (kWh/year)	PV capacity factor (%)	Wind turbine production (kWh/year)	Wind turbine capacity factor (%)	Fuel cell production (kWh/year)	Fuel cell capacity factor (%)	Converter capacity factor (%)	Converter losses (kWh/year)
Markazi	Arak	22	1642	18.7	167	0.8	114	1.3	11.1	51
Ardabil	Ardabil	77	1329	15.2	10919	49.9	41	0.2	1.9	9
Khuzestan	Ahvaz	35	1638	18.7	1648	7.53	100	1.2	8.7	40
Hormozgan	Bandarabbas	79	1691	19.3	11355	51.8	30	0.2	2.4	11
South Khorasan	Birjand	73	1730	19.8	8710	39.8	39	0.2	3.4	16
North Khorasan	Bojnord	65	1525	17.4	6921	31.6	53	0.2	4.1	19
Bushehr	Bushehr	71	1879	21.5	8299	37.9	47	0.2	3.8	17
Isfahan	Isfahan	66	1738	19.8	6945	31.7	49	0.2	3.9	18
Golestan	Gorgan	55	1434	16.4	4579	20.9	68	0.2	4.9	23
Hamedan	Hamedan	27	1637	18.7	673	3.07	109	0.2	10.2	47
Ilam	Ilam	60	1615	18.4	5367	24.5	72	0.2	4.8	22
Alborz	Karaj	70	1604	18.3	8013	36.6	52	0.2	3.6	16
Kerman	Kerman	36	1710	19.5	1660	7.58	84	0.2	8.9	41
Kermanshah	Kermanshah	67	1640	18.7	7236	33.0	55	0.2	3.6	17
Lorestan	Khorramabad	60	1691	19.3	5461	24.9	57	0.2	4.6	21
Razavi Khorasan	Mashhad	51	1531	17.5	3951	18.0	70	0.2	6.2	28
West Azerbaijan	Urmia	25	1599	18.2	519	2.37	120	0.2	10.2	47
Qazvin	Qazvin	71	1488	17.0	8422	38.5	55	0.2	3.2	15
Qom	Qom	70	1643	18.8	8023	36.6	51	0.2	3.6	17
Gilan	Rasht	74	1312	15.0	9745	44.5	51	0.2	2.5	11
Kordistan	Sanandaj	67	1604	18.3	7033	32.1	67	0.2	4.1	19
Mazandaran	Sari	55	1310	15	4919	22.5	73	0.2	4.6	21
Semnan	Semnan	58	1570	17.9	5169	23.6	59	0.2	4.6	21
Chaharmahal and Bakhtiari	Shahrekord	59	1599	18.3	5255	24.0	61	0.2	4.4	20
Fars	Shiraz	68	1744	19.9	7275	33.2	55	0.2	4.3	20
East Azerbaijan	Tabriz	75	1520	17.4	9692	44.3	54	0.2	2.7	13

Tehran	Tehran	71	1604	18.3	8409	38.4	52	0.2	3.6	17
Kohgiluyeh and Boyer-Ahmad	Yasuj	61	1712	19.5	5647	25.8	61	0.2	4.8	22
Yazd	Yazd	71	1763	20.1	8286	37.8	43	0.2	3.8	17
Sistan and Baluchistan	Zahedan	47	1736	19.8	3193	14.6	65	0.2	7.3	34
Zanjan	Zanjan	38	1556	17.8	2041	9.32	93	0.2	7.4	34

This analysis indicates that the results presented in Tables 4 and 5 provide a robust foundation for the subsequent multi-criteria ranking of provinces and offer clear justification for employing the TOPSIS method and Monte Carlo uncertainty analysis in the final evaluation of priority locations. Although converter loss values are reported in Table 5, these values are presented solely for the purpose of comparing the relative performance of the systems. The calculation of overall system efficiency and comprehensive reliability indicators such as LPSP and LOLP was beyond the scope of the present study and may be considered in future research.

The TOPSIS results (Fig. 4) indicate significant differences among provinces in terms of their proximity to the ideal solution. The calculated CCs suggest that certain provinces offer an optimal trade-off between lower costs, superior energy performance, reduced emissions, and favorable contextual conditions. Based on the final ranking, Tehran province achieved the highest CC (≈ 0.69) and was identified as the top choice. Following closely, the provinces of Alborz (Karaj), Razavi Khorasan (Mashhad), and Ardabil were ranked second through fourth, respectively. Additionally, provinces such as Yazd, Hormozgan, and Qom were also observed among the high-priority options, indicating their suitable potential for the deployment of hybrid renewable systems.

Although Hormozgan and Ardabil outperform Tehran in metrics like COE, NPC, and renewable share, these individual indicators do not dictate the final TOPSIS ranking. Instead, TOPSIS evaluates

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all ten weighted criteria simultaneously to determine the closeness coefficient. Thus, Tehran's top ranking reflects its balanced performance across all economic, environmental, and contextual factors, rather than dominance in any single indicator. Tehran simultaneously exhibits relatively low energy production costs, a high share of renewable energy, favorable utilization of wind and solar resources, a large population as a proxy for potential energy demand and infrastructure development, and suitable implementation conditions. The combined effect of these characteristics results in a higher closeness coefficient to the ideal solution than that of the other alternatives. Conversely, while Hormozgan and Ardabil excel in specific metrics, the aggregate influence of all criteria results in their lower scores. Thus, the final ranking represents a weighted multi-criteria compromise, not dominance in any single indicator.

In contrast, Kerman, Sistan and Baluchistan, and Hamadan were positioned at the bottom of the ranking, recording lower CC values. For instance, Kerman with a CC ≈ 0.28, demonstrated the lowest proximity to the ideal solution. These results imply that in these provinces, the combination of cost, performance, and contextual criteria is less favorable compared to other options, necessitating supportive policies, infrastructure improvements, or a revision of the system design.

The results reveal that the final ranking resulted from the combined influence of economic, environmental, energy-performance, and contextual criteria rather than the dominance of any single indicator. Meanwhile, energy performance criteria, particularly the renewable energy share and the capacity factors for wind and solar power, acted as reinforcing factors for the rank of provinces with high potential. On the other hand, contextual criteria such as population, natural disaster risk, and land price ensured that the results were not solely based on technical or economic optimality, but also incorporated implementation considerations and risk assessment into the final decision.

The graphical representation of the results, in the form of a ranking chart where bar length indicates the CC value and the number at the bar tip denotes the province's rank, facilitates quick and accurate visual comparison. The intensity of the bar colors was also employed to highlight performance differences between provinces, aiding in the clear distinction of superior and weaker options. This visual display, in addition to enhancing the readability of the results, is highly practical for presentation to non-technical policymakers and decision-makers.

Overall, the findings of this study demonstrate that the use of the TOPSIS method, combined with simulation data and contextual criteria, provides a powerful tool for the spatial prioritization of hybrid renewable systems. The resulting ranking can serve as a basis for decision-making in the initial stages of project site selection, identification of pilot provinces, allocation of investment incentives, and further analyses. Furthermore, the presented framework is readily expandable for scenario analysis and sensitivity assessment of criterion weights and can be utilized in future studies for comparing different MCDM methods or evaluating energy policies at the national scale.

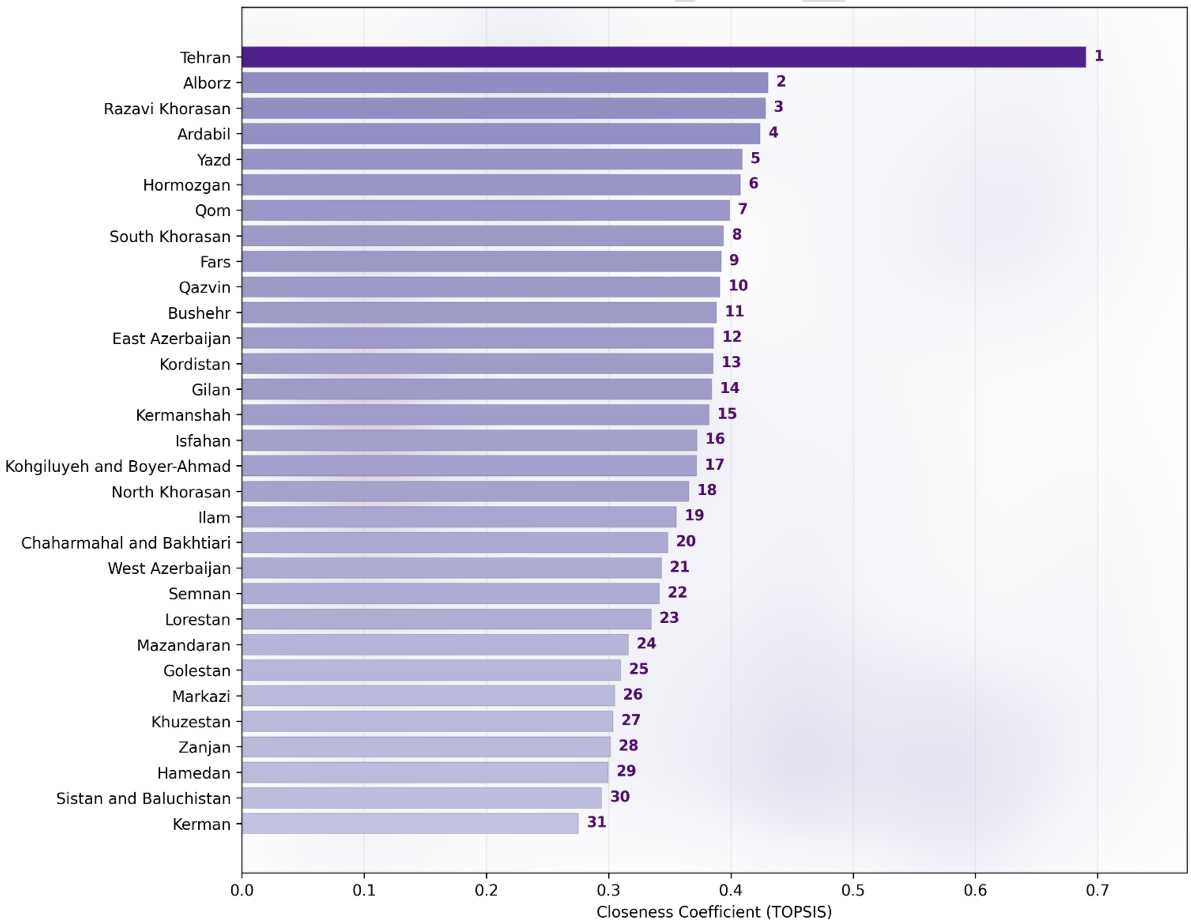

Fig. 4. Ranking of Iranian provinces for deployment of a solar-wind-fuel cell hybrid system based on the TOPSIS method

Monte Carlo analysis (10,000 iterations; ±20% uncertainty) confirms the stability of the provincial rankings (Fig. 5). Metrics including mean rank, standard deviation, and top-rank probability demonstrate that the leading provinces consistently maintain their positions across most scenarios, validating the robustness of the deterministic results.

Fig. 5 confirms Tehran as the most stable option, showing a mean rank near 1 and minimal standard deviation. This behavior indicates that even with random fluctuations of ±20% in the CC index, Tehran consistently remained among the top ranks in almost all scenarios. The observed stability can be attributed to the combined effect of favorable contextual criteria, a higher population as a proxy for regional importance and development potential, relatively low values of COE and NPC, as well as a higher share of renewable energy within the system's energy mix. Following Tehran, Alborz province (Karaj) and Razavi Khorasan province (Mashhad) also exhibit low mean ranks (approximately in the range of 2 to 3) and limited standard deviations, indicating the robustness of their positions against data uncertainty. In these two provinces, the favorable combination of wind capacity factor, relatively high wind turbine production, and high renewable share has played a decisive role in stabilizing their ranks. In contrast, provinces such as Fars (Shiraz), Qazvin (Qazvin), and South Khorasan (Birjand), although having relatively favorable mean ranks, exhibit larger rank standard deviations. This suggests that the position of these provinces improves in some scenarios but declines in others. From a system perspective, this behavior is related to the system's performance sensitivity to changes in wind or solar production and their interplay with cost indices (COE and NPC). Provinces like Kerman (Kerman) and Sistan and Baluchistan (Zahedan) are at the bottom of the ranking with high mean ranks (close to 30 and 31) and relatively limited dispersion, indicating that even in optimistic scenarios, their distance from the top options is maintained; this is primarily due to higher costs, greater CO_2 emissions, and a lower renewable share in the simulation outputs.

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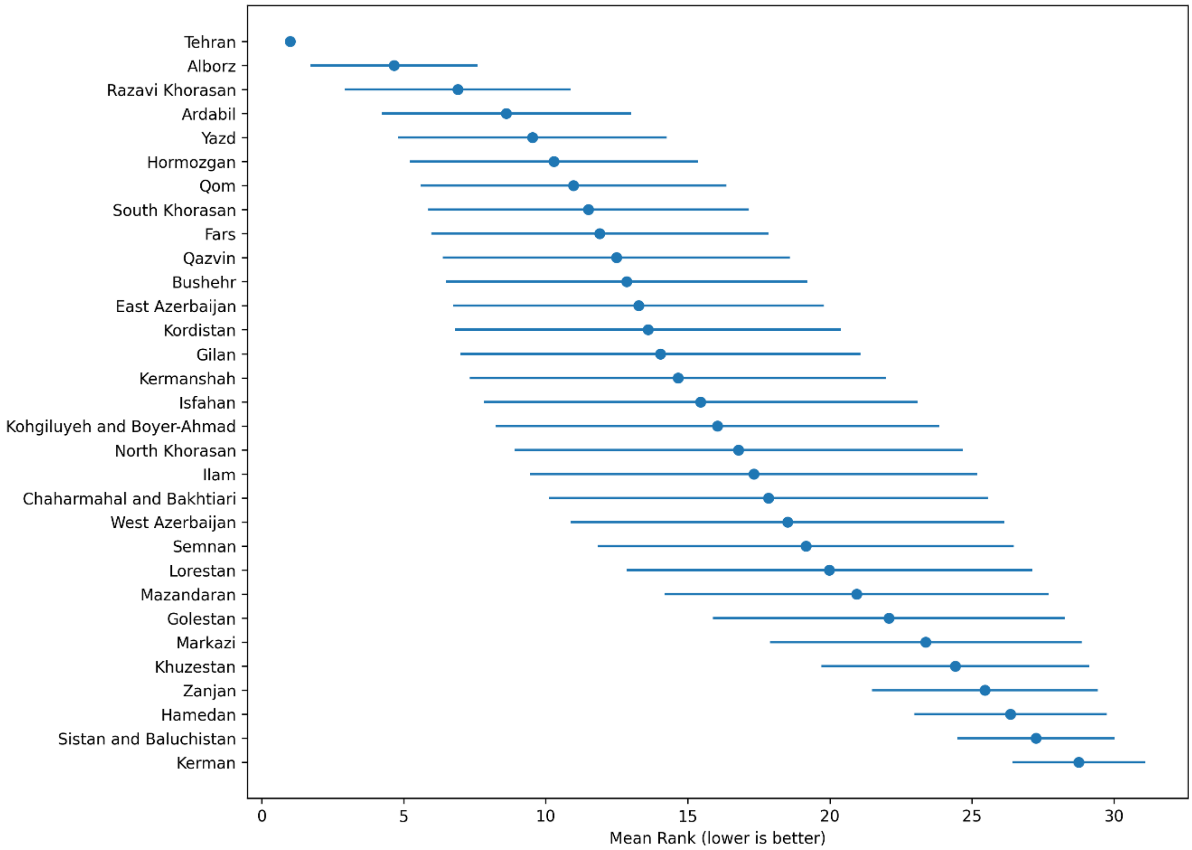

Fig. 5. Mean rank and rank standard deviation of Iranian provinces from Monte Carlo analysis (10,000 iterations with ±20% uncertainty range) for evaluating TOPSIS ranking stability

The analysis of Fig. 6 (Probability of being in Top-5 and Top-10) provides a more quantitative assessment of decision risk. The results show that Tehran province was ranked among the top five in over 90% of the 10,000 simulations and has a probability of almost 1 of being in the top ten. These figures indicate that selecting Tehran is a low-risk and highly reliable option from an energy decision-making perspective. Alborz province (Karaj) and Razavi Khorasan province (Mashhad) also have a high probability of being in the Top-5 (over approximately 60-70%) and a very high probability of being in the Top-10, confirming their positions as priority options. In contrast, provinces like Yazd (Yazd) and Hormozgan (Bandarabbas), although having a high probability of being in the Top-10, have a significantly lower probability of being in the Top-5. This difference suggests that these provinces are often at the upper edge of the ranking, and their entry or exit from the top five ranks is sensitive to data fluctuations and weighting changes. For intermediate provinces such as Isfahan (Isfahan) and East Azerbaijan (Tabriz), the probability of being in the Top-10 remains moderate, and

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the probability for the Top-5 is lower. This behavior indicates that these provinces are suitable options for an initial screening phase, but their final selection requires further analysis, such as policy scenario modeling or a review of local constraints. Conversely, provinces like Kerman and Sistan and Baluchistan have an almost zero probability of being in the Top-10, quantitatively confirming that these options lack competitiveness in most uncertainty scenarios.

Fig. 7 (Box plot of rank distribution for the top 15 provinces) offers a deeper insight into the ranking behavior of the provinces. For provinces like Tehran, Alborz, and Razavi Khorasan, very narrow boxes with medians close to ranks 1 to 3 are observed, indicating a high concentration of ranks and minimal dispersion. This means that even in the worst-case random scenarios, these provinces do not fall to the middle or lower ranks. In contrast, for provinces like Fars and Qazvin, the box length is larger, and the median is located at higher ranks; this implies that while these provinces perform well in some scenarios, they may drop several ranks in others. From a system perspective, this behavior is related to the simultaneous fluctuations of wind and solar generation and their impact on the final energy cost and renewable share.

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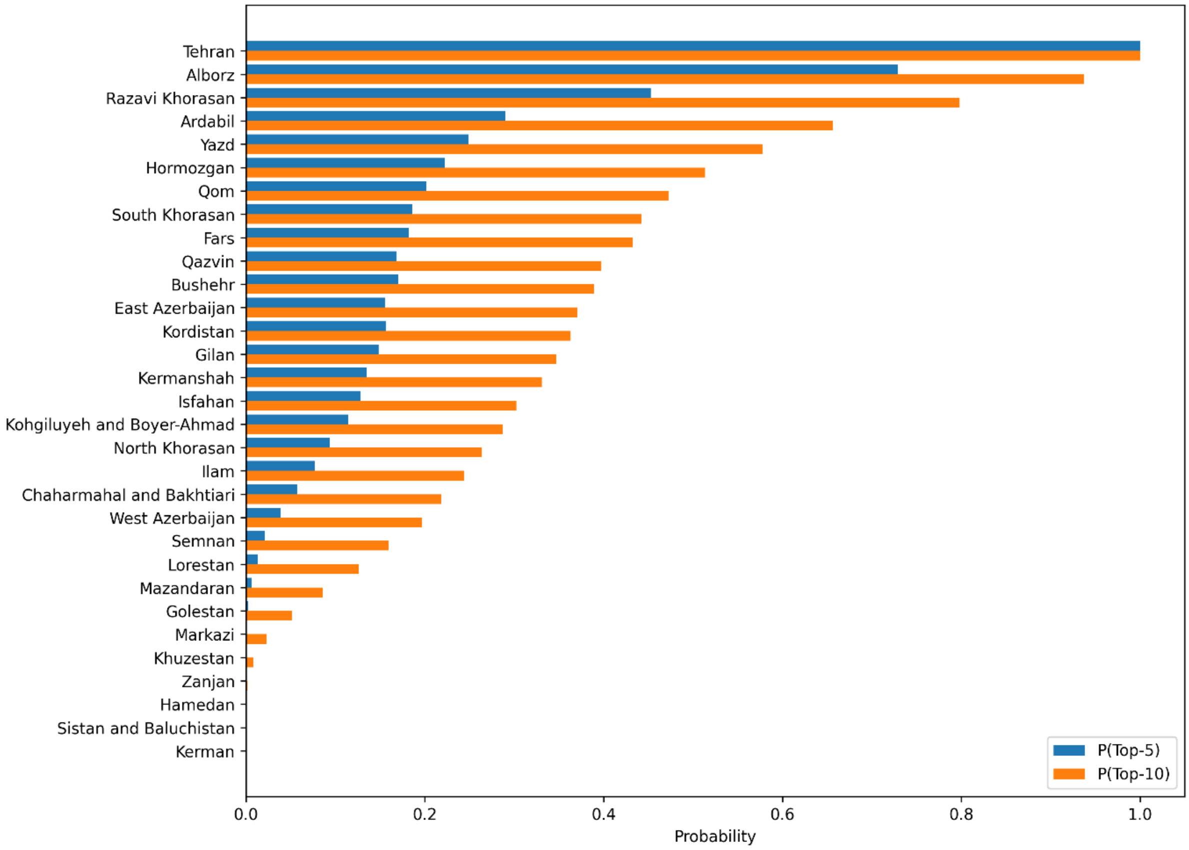

Fig. 6. Probability of Iranian provinces ranking in the top five and top ten based on Monte Carlo analysis (10,000 iterations with ±20% uncertainty range) for assessing decision risk and confidence

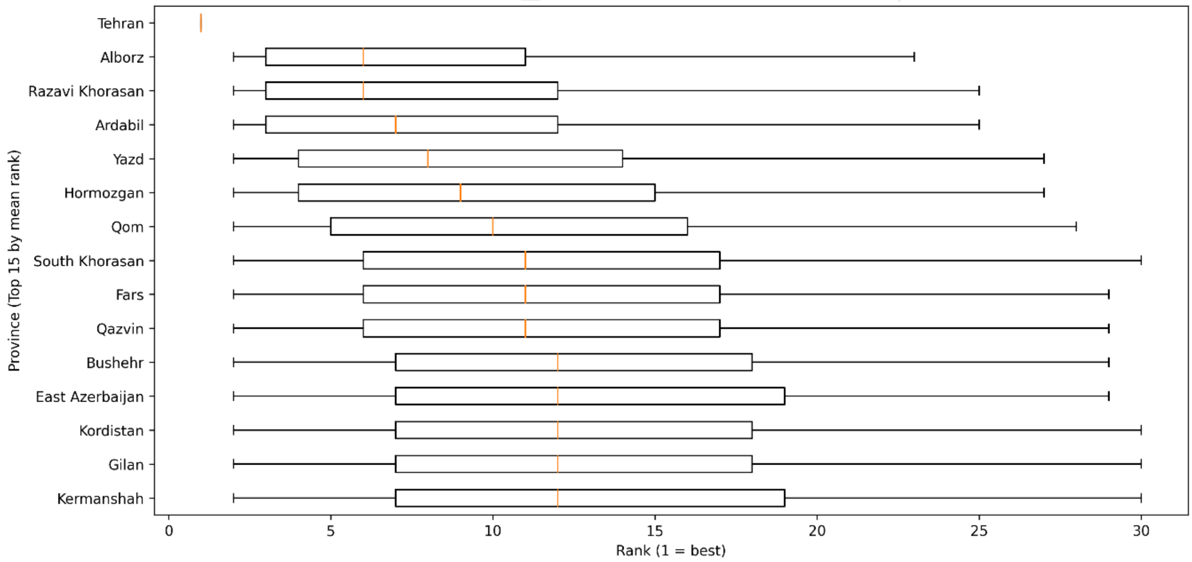

Fig. 7. Statistical distribution of ranks for the top 15 provinces based on Monte Carlo Analysis (10,000 iterations with ±20% uncertainty range) and assessing rank stability under data uncertainty

Overall, the quantitative and qualitative comparison of the three Monte Carlo plots shows that Tehran, Alborz, and Razavi Khorasan provinces not only have the highest deterministic ranks but are also

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statistically the most stable, lowest-risk, and most reliable options for deploying solar-wind-fuel cell hybrid systems. Yazd and Hormozgan offer high but sensitive potential, and could reach top-tier status with supportive policies or system optimization. Conversely, Kerman and Sistan and Baluchistan have shown weaker performance in most scenarios, and their selection is not technically or economically justifiable without policy support or system restructuring. These results indicate that combining TOPSIS ranking with Monte Carlo analysis not only provides a numerical prioritization but also enables risk-based decision-making, making it directly applicable to energy policymaking, pilot project site selection, and national-scale renewable energy system development planning.

To provide a more comprehensive assessment of ranking robustness, the empirical ranking distributions of all provinces obtained from 10,000 Monte Carlo simulation iterations were analyzed. The corresponding results are presented in Table 6, which reports not only the deterministic TOPSIS ranking but also the mean ranking, ranking standard deviation, 95% confidence interval, and the probability of each province appearing among the top five and top ten alternatives.

The results indicate that Tehran Province is the most stable alternative, consistently ranking first across all simulation iterations, with a mean ranking of 1.00, a ranking standard deviation of 0.00, and a 95% confidence interval of [1,1]. This demonstrates that Tehran's superiority over the remaining alternatives is completely robust with respect to the imposed uncertainty and remains unchanged under all simulated scenarios. In contrast, Alborz, Razavi Khorasan, and Ardabil, whose TOPSIS closeness coefficients were very close to one another, exhibited 95% confidence intervals of [2,18], [2,19], and [2,20], respectively. These results indicate that although these provinces consistently remained among the top-performing alternatives, their relative ranking positions may change under the imposed perturbations. Therefore, the majority of the ranking uncertainty is associated with permutations among alternatives having very similar TOPSIS closeness coefficients. On the other hand, the lowest-ranked provinces, including Kerman, Sistan and Baluchestan, Hamedan, and Zanjan, also remained within the lowest ranking positions despite experiencing minor changes in their exact rankings. For example, Kerman Province exhibited a mean ranking of 28.31 with a 95% confidence

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interval of [22,31], indicating that although its exact ranking may vary slightly, it consistently remains within the group of low-priority provinces under all simulated scenarios. Overall, the confidence interval analysis demonstrates that the imposed uncertainty primarily causes rank exchanges among alternatives with very similar performance, whereas provinces exhibiting either exceptionally strong or exceptionally weak performance retain their overall positions. Consequently, it can be concluded that the final TOPSIS ranking is sufficiently robust and reliable, and that the imposed uncertainty does not have a significant effect on the overall prioritization of the provinces.

Table 6. Statistical summary of provincial ranking distributions obtained from 10,000 Monte Carlo simulations, including mean rank, standard deviation, quartiles, and 95% confidence intervals

Province	Deterministic Rank	Mean Rank	SD	Q1	Median	Q3	95% CI
Tehran	1	1.00	0.00	1	1	1	[1,1]
Alborz	2	7.43	5.20	3	6	11	[2,18]
Razavi Khorasan	3	7.57	5.34	3	6	12	[2,19]
Ardabil	4	8.07	5.51	3	7	12	[2,20]
Yazd	5	9.69	6.14	4	8	14	[2,22]
Hormozgan	6	9.86	6.16	4	8	14	[2,22]
Qom	7	10.87	6.35	5	10	16	[2,23]
South Khorasan	8	11.61	6.56	6	11	17	[2,24]
Fars	9	11.96	6.60	6	11	17	[2,24]
Qazvin	10	12.06	6.60	6	11	17	[3,25]
Bushehr	11	12.43	6.65	7	12	18	[3,25]
East Azerbaijan	12	12.88	6.74	7	12	18	[3,25]
Kordistan	13	12.75	6.68	7	12	18	[3,25]
Gilan	14	12.90	6.74	7	12	18	[3,25]
Kermanshah	15	13.22	6.76	8	13	19	[3,26]
Isfahan	16	14.64	6.77	9	14	20	[4,27]
Kohgiluyeh & Boyer-Ahmad	17	14.73	6.89	9	14	20	[4,27]
North Khorasan	18	15.70	6.85	10	16	21	[5,28]
Ilam	19	17.29	6.73	12	18	23	[6,28]
Chaharmahal & Bakhtiari	20	18.27	6.70	13	19	24	[7,29]
West Azerbaijan	21	19.01	6.56	14	20	25	[8,29]
Semnan	22	19.34	6.50	14	20	25	[8,29]
Lorestan	23	20.38	6.32	16	21	26	[9,30]
Mazandaran	24	23.10	5.55	20	24	28	[12,31]
Golestan	25	24.22	5.14	21	25	28	[14,31]
Markazi	26	24.68	4.90	22	25	29	[15,31]
Khuzestan	27	25.02	4.79	22	26	29	[15,31]
Zanjan	28	25.26	4.68	23	26	29	[15,31]
Hamedan	29	25.53	4.52	23	26	29	[16,31]
Sistan & Baluchistan	30	26.22	4.16	24	27	29	[17,31]
Kerman	31	28.31	2.89	27	29	31	[22,31]

The quartile analysis further confirms the same findings. For Tehran Province, the values of Q1, Median, and Q3 are all equal to 1, indicating complete stability of the first ranking position across all simulation iterations. In contrast, the top-ranked provinces, including Alborz, Razavi Khorasan, and Ardabil, exhibit larger interquartile ranges, indicating that although these provinces consistently remain among the highest-ranked alternatives, their relative positions within the top group may vary. Likewise, for the lowest-ranked provinces, such as Kerman, the fact that Q1, Median, and Q3 all lie within the lower ranking positions indicates that, despite minor ranking fluctuations, these provinces consistently remain within the group of low-priority alternatives. Overall, the quartile statistics demonstrate that the imposed uncertainty primarily results in rank exchanges among alternatives with similar performance, while leaving the overall prioritization structure essentially unchanged.

6. Research Limitations and Future Research Directions

One limitation of the present study is that all HOMER simulations were conducted based on a standard hybrid system configuration and a common benchmark load profile applied uniformly across all provinces. Therefore, the resulting economic indicators, including COE and NPC, were primarily used to compare the relative performance of provinces and to support their spatial prioritization. These indicators should not be interpreted as direct estimates of energy supply costs or infrastructure requirements at the actual provincial scale. Future studies are recommended to incorporate province-specific electricity consumption patterns, capacity expansion scenarios, and grid constraints in order to provide more accurate and practically applicable results for regional-scale energy planning.

Another limitation of this study is related to the uncertainty modeling approach. In the present Monte Carlo analysis, parameter variations were treated independently, and potential correlations among economic, performance, and climatic variables were not modeled. Therefore, the results primarily reflect the relative stability of the ranking against data fluctuations rather than the full uncertainty behavior of the system. Future studies are encouraged to employ methods such as correlation matrix-based Monte Carlo simulation, Latin Hypercube Sampling (LHS), copula-based models, and global sensitivity analysis to more comprehensively investigate the effects of variable dependencies.

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Another limitation of this study is related to the uncertainty propagation strategy. The Monte Carlo analysis was performed by introducing variations in the TOPSIS Closeness Coefficient rather than propagating uncertainties from the primary input variables through the HOMER simulations. Consequently, uncertainties associated with parameters such as wind speed, solar radiation, land price, population, and other technical and economic inputs were not directly modeled throughout the simulation process. Therefore, the reported results should be interpreted primarily as an assessment of the robustness and stability of the provincial rankings with respect to variations in the final decision-making indicator, rather than as a comprehensive representation of uncertainty propagation across the entire energy system. Future studies may establish a more comprehensive uncertainty framework by assigning probabilistic distributions to the primary input variables and propagating these uncertainties from the HOMER simulation stage through to the multi-criteria decision-making process.

Although converter losses are reported in this study, the calculation of Overall System Efficiency was beyond the scope of the present research. The primary objective of this study was to evaluate and comparatively rank Iranian provinces based on technical, economic, environmental, and location-related indicators. Therefore, the analysis focused on metrics such as COE, NPC, Renewable Fraction, and other criteria employed in the TOPSIS framework. In addition, reliability indicators including Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), and Deficiency of Power Supply were not calculated. Consequently, the reported converter loss values are intended solely for the relative comparison of system performance across different provinces and should not be interpreted as a basis for a comprehensive assessment of the overall energy efficiency of the system. Future studies are recommended to utilize detailed HOMER outputs to calculate and evaluate overall system efficiency, reliability indicators, and a comprehensive analysis of energy losses.

Overall, an important direction for future research is to develop integrated uncertainty analysis frameworks that simultaneously account for both uncertainty propagation from the primary input variables and the statistical dependencies among technical, economic, environmental, and climatic parameters. Future studies are also encouraged to determine the uncertainty range of each input variable based on long-term historical data or parameter-specific probability distributions and subsequently propagate these uncertainties throughout the entire analysis chain, from the HOMER simulations to the construction of the decision matrix, the implementation of the TOPSIS method, and the final ranking of alternatives. Such frameworks would enable a more comprehensive evaluation of the robustness and reliability of hybrid energy system planning and provincial prioritization.

7. Conclusion

The study results reveal that national-scale planning and siting of renewable hybrid energy systems, particularly multi-source configurations such as solar-wind-fuel cell systems, is a multidimensional, heterogeneous, and uncertainty-driven problem that cannot be adequately addressed by a single technical or economic indicator. The climatic diversity, population differences, environmental risks, and economic considerations across the provinces of Iran mean that decisions based on averages or single-scenario analyses do not provide an accurate picture of true development priorities. Therefore, a primary objective of this research was to develop a coherent analytical framework capable of simultaneously incorporating the system's technical performance, costs, environmental impacts, and contextual conditions into the decision-making process, while also evaluating the robustness of the results against data uncertainty. In this regard, this paper presents an integrated, risk-based decision-making framework whose contributions can be articulated at three levels: scientific, applicative, and operational. Scientifically, integrating HOMER simulation results with TOPSIS and Monte Carlo uncertainty analysis provides an approach beyond deterministic ranking, enabling statistical analysis of rank stability. From an applicative perspective, this framework enables the simultaneous consideration of economic, environmental, performance, and contextual criteria in provincial prioritization. Operationally, the research outputs are directly applicable to policymakers, planning agencies, and energy decision-makers for pilot-region selection and resource allocation.

The research methodology was designed in a phased and coherent manner. First, the performance of the solar-wind-fuel cell hybrid system was simulated for provincial centers using HOMER software, and technical, economic, and environmental indicators were extracted. Second, these indicators, along

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with contextual criteria, were used within the TOPSIS framework to rank the provinces. Finally, to evaluate the sensitivity and stability of the results, Monte Carlo simulations with multiple iterations were performed to analyze the probability distribution of ranks and decision risk. The parameters considered in this study included the COE, total NPC, CO_2 emission levels, renewable energy share, solar and wind resource capacity factors, population, natural disaster risk, and land price, covering a comprehensive set of technical and contextual considerations.

The key findings of this study are structured around quantitative, qualitative, and comparative insights as follows:

- Quantitatively, Tehran achieved the highest CC and ranked among the top five provinces in over 90% of the Monte Carlo simulations, indicating strong stability under parameter uncertainty.
- Quantitatively, Kerman and Sistan and Baluchistan ranked low in most scenarios despite strong solar or wind potential, owing to unfavorable economic and contextual conditions.
- Qualitatively, the results showed that renewable resource potential alone cannot guarantee high deployment priority, as population and risk-based indicators play a decisive role in the final ranking.
- Comparatively, comparing deterministic TOPSIS rankings with Monte Carlo results revealed that some provinces occupy borderline and unstable positions that could be misclassified without uncertainty analysis.
- Overall, the proposed framework distinguishes between low- risk and high-risk provinces, providing a more reliable basis for decision-making.

In summary, the results demonstrate that integrating simulation, MCDM, and uncertainty analysis substantially improves decision-making for renewable hybrid energy system development, reducing the risk of oversimplified and potentially misleading choices. The framework is applicable not only to Iran but also to other countries with diverse climates and heterogeneous regional conditions.

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Finally, future research could extend the framework to hybrid systems combining battery storage with fuel cells, apply advanced data-driven or machine learning-based weighting methods, incorporating dynamic scenarios for demand and energy price variations, and integrating social and institutional dimensions into the decision process. These developments could further enhance the accuracy, comprehensiveness, and practical effectiveness of the proposed framework.

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