

Article

A Fuzzy Multi-Criteria Framework for Sustainability Assessment of Wind–Hydrogen Energy Projects: Method and Case Application

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Abstract

This study develops a comprehensive framework for assessing the sustainability performance of wind power systems integrated with hydrogen storage (WPCHS). Unlike previous works that mainly emphasized economic or environmental indicators, our approach incorporates a balanced set of economic, environmental, and social criteria, supported by expert evaluation. To address the uncertainty in human judgment, we introduce an interval-valued fuzzy TOPSIS model that provides a more realistic representation of expert assessments. A case study in Manjil, Iran, demonstrates the application of the model, highlighting that project A_4 outperforms other alternatives. The findings show that both economic factors (e.g., levelized cost of energy) and social aspects (e.g., poverty alleviation) strongly influence project rankings. Compared with earlier studies in Europe and the Middle East, this work contributes by extending the evaluation scope beyond financial and environmental metrics to include social sustainability, thereby enhancing decision-making relevance for policymakers and investors.

Keywords: wind power coupling hydrogen storage (WPCHS) project; sustainability; multi-criteria decision making (MCDM); interval-value fuzzy number



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1. Introduction

Iran's energy sector remains heavily reliant on fossil fuels, with crude oil and natural gas shaping its economic foundation. However, excessive dependence on fossil resources has led to severe environmental challenges, such as air pollution, greenhouse gas emissions, and ecological degradation [1,2]. In response, global and national energy transitions increasingly emphasize renewable energy. Iran has favorable wind conditions, yet its installed wind capacity is still modest compared to regional peers [3]. One of the central barriers to large-scale wind integration is intermittency, which undermines grid stability [4]. Hydrogen energy storage has emerged as a promising solution for addressing variability, offering long-duration storage capacity, conversion flexibility, and decarbonization potential [5,6]. While numerous studies have analyzed the techno-economic feasibility of wind–hydrogen systems [7–14], most have concentrated on cost-effectiveness or life-cycle emissions. Few works have provided a holistic assessment that also includes social sustainability dimensions such as job creation, poverty alleviation, or public acceptance [15,16].

This study advances the literature by developing an interval-valued fuzzy TOPSIS framework that evaluates WPCHS projects across economic, environmental, and social dimensions. Compared with earlier approaches that relied on deterministic methods or focused narrowly on quantitative indicators, the proposed model captures uncertainty in expert judgment and incorporates qualitative aspects critical to long-term sustainability. By applying this model to a real case in Iran, the study not only validates methodological robustness but also generates practical insights for decision-makers.

The remainder of this paper is structured as follows. Section 2 reviews the recent literature on wind–hydrogen projects and sustainability assessment methods. Section 3 introduces the technological background of Wind Power Coupled Hydrogen Storage (WPCHS) systems. Section 4 outlines the sustainability criteria framework, covering economic, environmental, and social dimensions. Section 5 presents the proposed interval-valued fuzzy TOPSIS model in detail. Section 6 demonstrates the model’s application through a case study in the Manjil region of Iran. Section 7 discusses the results, compares them with alternative approaches, and highlights managerial implications. Finally, Section 7 concludes the paper, summarizing key findings and suggesting directions for future research.

2. Literature Review

In recent years, wind–hydrogen systems have gained increasing global attention as a pathway to enhance renewable energy integration and sustainability. The existing literature can be grouped into three main streams: economic feasibility studies, environmental assessments, and methodological frameworks. From an economic perspective, several studies have evaluated the cost-effectiveness of WPCHS. Schuster and Walther [7] applied a decision tree in Germany, showing that direct re-electrification was not profitable, but hydrogen sales under certain conditions offered attractive returns. Loisel et al. [8] found that hydrogen storage integration reduced wind curtailment by nearly one-third in offshore projects. Siyal et al. [9] evaluated wind-based hydrogen refueling stations and reported significant variation in hydrogen cost depending on site and turbine type. More recently, Qolipour et al. [13] and Al-Sharafi et al. [14] analyzed hybrid solar–wind–hydrogen systems in Iran and Saudi Arabia, respectively, demonstrating promising economic potential.

On the environmental side, life cycle assessments (LCAs) have quantified reductions in greenhouse gas emissions and other ecological impacts. Ghandehariun and Kumar [10] highlighted the carbon benefits of wind-based hydrogen in Canada, while Ji-Yong et al. [11] integrated life cycle costing with LCA to assess hydrogen stations powered by wind. Beyond emissions, researchers have started to expand environmental evaluations to include water consumption, material intensity, and ecological trade-offs, which are increasingly relevant for large-scale deployment [17,18].

Despite these contributions, the social dimension of sustainability has been largely underexplored. WPCHS projects have strong potential to create jobs, alleviate poverty, and increase public acceptance of renewable energy [19,20], yet few studies explicitly quantify or integrate these effects into decision models. Hacetoglu et al. [15,16] proposed a sustainability index for hydrogen-based systems, but their framework emphasized quantitative indicators and did not sufficiently address qualitative social factors. To fill these gaps, researchers have increasingly adopted multi-criteria decision-making (MCDM) methods. Classical tools such as AHP, TOPSIS, and VIKOR have been widely used for renewable energy site selection, supplier evaluation, and technology prioritization [21–25]. These methods enable simultaneous consideration of economic, environmental, and social indicators. However, one key challenge remains: capturing uncertainty and subjectivity in expert judgments, particularly when dealing with qualitative or linguistic criteria (e.g., high public acceptance vs. low public acceptance).

Fuzzy set theory, introduced by Zadeh [26], provides a robust solution for modeling imprecision in decision-making. Applications of fuzzy AHP-TOPSIS have been reported in construction risk assessment [27], organizational capability evaluation [28], and maritime logistics [29]. More recently, scholars have advanced to interval-valued and type-2 fuzzy approaches, which allow for richer representation of uncertainty and conflicting expert opinions [30–32]. Recent studies have emphasized that ecological efficiency, particularly when linked with green technology innovation, is an essential dimension of sustainability evaluation. For example, Du et al. [33] assessed ecological efficiency under low-carbon city construction and highlighted the decisive role of innovation in shaping environmental outcomes. This perspective supports the inclusion of ecological and innovation-related criteria in our framework. Yet only a handful of works have applied such advanced fuzzy methods to the sustainability assessment of WPOCHS. This study addresses the above shortcomings by proposing an interval-valued fuzzy TOPSIS (IVF-TOPSIS) framework that integrates economic, environmental, and social criteria in a balanced manner. Compared to prior works, the novelty lies in:

1. Explicitly including social sustainability indicators (e.g., poverty alleviation, residential satisfaction).
2. Applying an interval fuzzy approach to better capture uncertainty in expert evaluations.
3. Demonstrating the method with a real-world case study in Iran, thereby contributing context-specific evidence to the global WPOCHS literature.

Recent research in Europe and the Middle East has highlighted the growing importance of wind-powered hydrogen systems. In Italy, techno-economic assessments of offshore wind-to-hydrogen plants in Sicily and the Adriatic region reported feasible levelized hydrogen costs of about €5–6/kg and electricity generation costs of €70–80/MWh, confirming their competitiveness under favorable conditions [34]. Other studies in Southern Italy found levelized hydrogen costs between €2.66 and €10/kg, depending on scale and transport assumptions [35]. In Turkey, investigations of onshore and offshore wind-to-hydrogen integration identified several high-potential regions (e.g., Erzurum, Van), with projections demonstrating significant expansion capacity for green hydrogen exports in the long term [36]. Similarly, studies across the Middle East and North Africa (MENA) region show promising cost-effectiveness. Gado et al. [37] reported that Egypt and Oman can achieve levelized costs of USD 5.34–6.18/kg for wind-based hydrogen production, outperforming other regional options in terms of both economics and carbon mitigation. A comparative study between Poland and Iraq also revealed that Middle Eastern sites can produce hydrogen more cheaply (USD 6.54–12.66/kg) than their European counterparts (USD 9.88–14.31/kg) due to superior resource availability and lower land and labor costs [38]. Taken together, these findings confirm that wind–hydrogen systems are gaining recognition worldwide as feasible pathways for energy transition. Our case study in Manjil, Iran, aligns with these global and regional trends by demonstrating both strong economic viability and site-level feasibility, while also addressing sustainability criteria under uncertainty.

3. Introduction to WPOCHS Technology

The Wind Power Coupled Hydrogen Storage (WPOCHS) system is an integrated solution designed to enhance the reliability and sustainability of wind energy through hydrogen storage technology. This system leverages surplus wind-generated electricity to produce hydrogen via electrolysis, which can then be stored and utilized when energy demand exceeds supply or when wind conditions are suboptimal. The WPOCHS framework comprises five primary subsystems that operate in synergy to ensure system functionality and energy efficiency:

Control Subsystem: Equipped with power electronic control units, including AC rectifiers and safety mechanisms, this component oversees system operation and stability.

Electrolytic Hydrogen Production Subsystem: This unit features a medium-pressure alkaline electrolyzer, hydrogen–oxygen separator, and balance valves. It facilitates water electrolysis to produce hydrogen gas, a process central to energy storage.

Storage Subsystem: The produced hydrogen is stored in both medium- and high-pressure tanks, enabling short- and long-term storage capacities and contributing to energy supply flexibility.

Compression Subsystem: This unit compresses the hydrogen gas to the required pressure levels for storage or transportation, improving volumetric efficiency and logistical feasibility.

Auxiliary Subsystem: This includes essential components such as scrubbers, separators, cooling systems, temperature and pressure controls, pumps, and ventilation systems—all supporting continuous and safe operation.

These interconnected subsystems collectively enable WPCHS to serve as a robust buffer between variable wind energy input and stable power output, thus enhancing grid reliability and promoting renewable energy integration. Hydrogen production via electrolysis involves the use of electricity to split water molecules into hydrogen and oxygen gases. Various electrolyzer technologies exist, namely, alkaline, proton exchange membrane (PEM), and solid oxide electrolysis cells (SOECs) [39,40]. Among these, alkaline electrolysis is the most established method, recognized for its technological maturity, operational simplicity, and favorable cost-performance ratio. Due to its compatibility with intermittent renewable sources like wind, alkaline electrolysis remains the preferred option in large-scale WPCHS implementations. Integrating hydrogen storage with wind power offers multiple advantages. It mitigates curtailment of excess wind energy, supports load balancing, and enables decarbonization of sectors such as transport and industry. Furthermore, the ability to store renewable electricity in chemical form allows for seasonal energy shifting and strategic energy reserve formation, addressing both technical and policy-driven challenges in renewable energy systems [5,6,39].

The integration of hydrogen storage with wind energy offers multiple benefits: reducing curtailment, enabling seasonal shifting of renewable electricity, stabilizing voltage fluctuations, and providing clean fuels for industry and transport. However, challenges such as energy losses during conversion, infrastructure costs, and safety considerations (e.g., leakage risks) remain critical issues that must be addressed in project planning.

4. Selection of Sustainable Criteria

Establishing a well-structured and comprehensive evaluation framework is essential for effectively assessing the sustainability performance of WPCHS (Wind Power Coupled Hydrogen Storage) projects. This study develops a three-dimensional criteria system, encompassing economic, environmental, and social aspects, aligned with the broader concept of sustainability in energy systems [19,41]. To formulate this framework, a two-stage approach was employed. First, an extensive review of the relevant academic literature was conducted to identify potential indicators across the three sustainability pillars [7–16]. Second, a panel of domain experts specializing in energy economics, environmental engineering, and energy-related social studies was consulted. The experts critically assessed the relevance and importance of each criterion. Based on their feedback, the initial list was refined, retaining only the most impactful indicators. The resulting criteria system is categorized as follows:

4.1. Economic Criteria (C1)

Investment Cost (C11): Includes expenditures on land acquisition, equipment (e.g., wind turbines, hydrogen storage units), construction, and labor. This criterion reflects the upfront financial commitment required for project deployment.

Operation and Maintenance Cost (C12): Covers the ongoing expenses related to staffing, routine servicing, spare parts, and operational support systems. These costs influence long-term financial sustainability.

Levelized Cost of Energy—LCOE (C13): Represents the net present value of the total cost of electricity generation per unit over the project's lifespan. LCOE is widely used for comparative economic assessment in the energy sector [9].

Payback Period (C14): Indicates the time required to recover the initial investment through project-generated revenues or savings. Investors often prioritize shorter payback durations to minimize financial risk.

4.2. Environmental Criteria (C2)

Carbon Dioxide Emission Reduction (C21): Evaluates the mitigation of greenhouse gases such as CO₂ and CH₄ through WPCHS implementation, relative to fossil-based power plants [10,11].

PM2.5 Emission Reduction (C22): Measures the reduction in fine particulate matter, a key contributor to urban air pollution and public health risks. Cleaner energy systems offer considerable improvements in this area.

Ecological Impact (C23): Assesses the extent of environmental disruption caused by project development, including vegetation loss, water depletion, soil erosion, and biodiversity decline [15,16].

Land Occupation (C24): Reflects the physical footprint of WPCHS installations. Projects with large land demands, especially in ecologically sensitive or urban-adjacent areas, may face increased costs or opposition.

Water footprint (C25): Hydrogen production through electrolysis consumes freshwater, which is especially important in arid regions such as Iran. Including this criterion highlights potential trade-offs between renewable energy deployment and water security.

Hydrogen leakage risk (C26): Hydrogen is a small-molecule gas that is prone to leakage. Although not directly harmful, it may indirectly influence atmospheric chemistry and contribute to greenhouse gas effects. Addressing this risk strengthens the environmental comprehensiveness of the framework.

4.3. Social Criteria (C3)

Poverty Alleviation Promotion (C31): Explores the project's contribution to local economic development and employment generation, which can reduce poverty levels and support government welfare initiatives [17].

Technological Innovation Promotion (C32): Assesses how the WPCHS project fosters advancements in clean energy technologies, particularly in hydrogen production, storage, and integration [6,20].

Power Quality Improvement (C33): Evaluates the system's effectiveness in stabilizing electricity supply by mitigating wind energy intermittency, voltage fluctuations and grid disturbances [4,5].

Residential Satisfaction (C34): Reflects public perception and acceptance of WPCHS projects. Community opposition, often rooted in concerns about land use or environmental impact, can hinder implementation; thus, public engagement and satisfaction are critical [42].

Social equity (C35): This criterion evaluates whether the benefits of WPOCHS projects (such as job creation, cleaner air, and access to affordable energy) are equitably distributed across communities. Including social equity responds to the growing emphasis on fairness and justice in sustainability transitions.

This sustainability criteria framework provides a robust foundation for evaluating WPOCHS project performance. By integrating both quantitative and qualitative indicators, it allows for holistic decision-making and supports strategic planning in the transition to clean energy.

5. Proposed Model

In decision-making scenarios involving uncertainty and imprecise expert judgment, traditional crisp numerical methods often fall short in capturing the nuances of human reasoning. To address this limitation, fuzzy set theory, as introduced by Zadeh [26], provides a mathematical framework for incorporating vagueness and subjectivity into decision processes. In fuzzy multi-criteria decision-making (MCDM), both the evaluation of alternatives and the assignment of criterion weights are expressed using fuzzy numbers. In this study, we employ interval-valued triangular fuzzy numbers (IVTFNs) to represent expert opinions. Each linguistic term (e.g., *low*, *medium*, *high*) is expressed as an interval triangular fuzzy number, which allows experts to define not only a central value but also a range of possible values around it. This reduces information loss and increases the realism of the evaluation process. Each linguistic term (e.g., *medium*, *high*) is represented by an interval of triangular fuzzy numbers, enabling more flexible and realistic modeling of expert evaluations. It is assumed that the $\tilde{X} = [\tilde{x}_{ij}]_{n \times m}$ shows the decision matrix where $\tilde{x}_{ij}$ represent the performance of alternative i (A_i) under criterion j (C_j), and n is the number of alternatives and m is the number of criteria. Therefore, the performance of alternative i relative to criterion j is determined by $\tilde{x}_{ij}$. According to Figure 1, $\tilde{x}_{ij}$ and $\tilde{w}_j$ is expressed as triangular interval fuzzy numbers.

$$\tilde{x} = [(x_1, x_2, x_3)(x'_1, x_2, x'_3)]$$

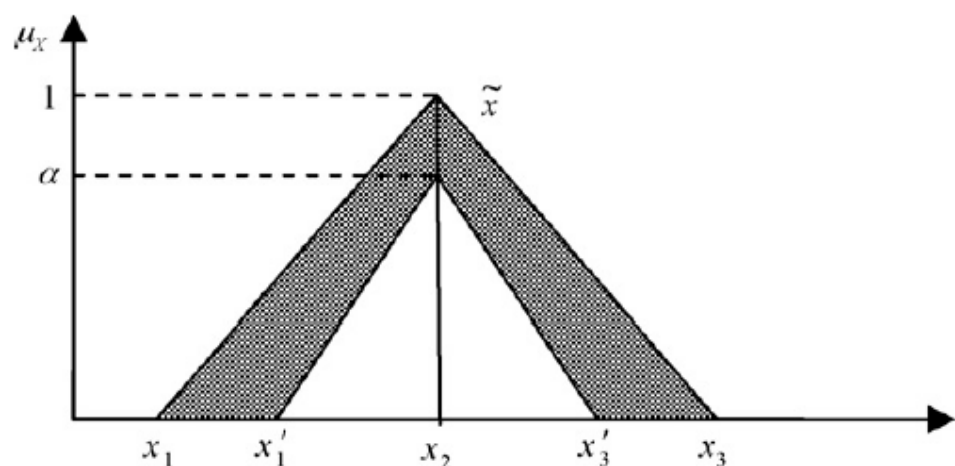


Figure 1. Triangular interval fuzzy number.

$\tilde{x}$ can be represented as $\tilde{x} = [(x_1, x'_1); x_2; (x'_3, x_3)]$, which allows professionals to express opinions about criteria and alternatives at a distance from the minimum and maximum. When multiple experts (K people) provide input, their judgments are aggregated

using the arithmetic mean approach to form a consensus fuzzy decision matrix. The aggregation formula is as follows:

$$\begin{aligned}\tilde{x}_{ij} &= \frac{1}{K} \left[\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \cdots + \tilde{x}_{ij}^K \right] \\ \tilde{w}_{ij} &= \frac{1}{K} \left[\tilde{w}_{ij}^1 + \tilde{w}_{ij}^2 + \cdots + \tilde{w}_{ij}^K \right]\end{aligned}\quad (1)$$

The above equation shows the average of $\tilde{x}_{ij}$ and $\tilde{w}_{ij}$ expert opinions. (+) represents fuzzy sum and hence the values $\tilde{x}_{ij}$ and $\tilde{w}_{ij}$ become fuzzy. Now, we are ready to present the proposed method. Suppose Ω_b and Ω_c show the set of benefit criteria and cost criteria, respectively. The steps of the proposed method are described below:

- i. To standardize the fuzzy decision matrix, normalization is carried out differently for benefit and cost criteria. For benefit criteria, higher values are preferred, while for cost criteria, lower values are favorable. Let $\tilde{x}_{ij} = \left[\left(a_{ij}, a'_{ij} \right); b_{ij}; \left(c'_{ij}, c_{ij} \right) \right]$ shows the (i, j) component of decision matrix, the normalized decision matrix is calculated as follows:

$$\begin{aligned}\tilde{r}_{ij} &= \left[\left(\frac{a_{ij}}{c_j^+}, \frac{a'_{ij}}{c_j^+} \right); b_{ij}; \left(\frac{c'_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \right] \quad i = 1, \dots, n, \quad j \in \Omega_b \\ \tilde{r}_{ij} &= \left[\left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c'_{ij}} \right); \frac{a_j^-}{b_{ij}}; \left(\frac{a_j^-}{a'_{ij}}, \frac{a_j^-}{a_{ij}} \right) \right] \quad i = 1, \dots, n, \quad j \in \Omega_c\end{aligned}\quad (2)$$

where

$$\begin{aligned}c_j^+ &= \max\{c_{ij}\}, \quad j \in \Omega_b \\ a_j^- &= \min\{a'_{ij}\}, \quad j \in \Omega_c\end{aligned}$$

- ii. The weighted normalized matrix can be obtained according to the different importance of the criteria. This matrix is denoted by $\tilde{V} = [\tilde{v}_{ij}]_{n \times m}$ and $\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j$. According to the definition of multiplication of fuzzy numbers, the weight normalization matrix can be written as follows:

$$\begin{aligned}\tilde{v}_{ij} &= \left[\left(\tilde{r}_{1ij} \times \tilde{w}_{1j}, \tilde{r}'_{1ij} \times \tilde{w}'_{1j} \right); \tilde{r}_{2ij} \times \tilde{w}_{2j}; \left(\tilde{r}'_{3ij} \times \tilde{w}'_{3j}, \tilde{r}_{3ij} \times \tilde{w}_{3j} \right) \right] \\ &= \left[\left(g_{ij}, g'_{ij} \right); h_{ij}; \left(l_{ij}, l'_{ij} \right) \right]\end{aligned}\quad (3)$$

- iii. Positive and negative ideal solutions in this study are defined as follows:

$$\begin{aligned}A^+ &= [(1, 1); 1; (1, 1)], \quad j \in \Omega_b \\ A^- &= [(0, 0); 0; (0, 0)], \quad j \in \Omega_c\end{aligned}\quad (4)$$

- iv. Euclidean distance can be calculated by the following formula:

$$\begin{aligned}D^-(\tilde{N}, \tilde{M}) &= \sqrt{\frac{1}{3} \sum_{i=1}^3 \left[(N_{x_i}^- - M_{y_i}^-)^2 \right]} \\ D^+(\tilde{N}, \tilde{M}) &= \sqrt{\frac{1}{3} \sum_{i=1}^3 \left[(N_{x_i}^+ - M_{y_i}^+)^2 \right]}\end{aligned}\quad (5)$$

$D^-(\tilde{N}, \tilde{M})$ and $D^+(\tilde{N}, \tilde{M})$ is times the first and second distance measurements. Therefore, the distance of each alternative from the positive and negative ideals is obtained as follows:

$$\begin{aligned} D_{i1}^+ &= \sqrt{\frac{1}{3} [(g_{ij} - 1)^2 + (h_{ij} - 1)^2 + (l_{ij} - 1)^2]} \\ D_{i2}^+ &= \sqrt{\frac{1}{3} [(g'_{ij} - 1)^2 + (h_{ij} - 1)^2 + (l'_{ij} - 1)^2]} \end{aligned} \quad (6)$$

Distance from negative ideals includes:

$$\begin{aligned} D_{i1}^- &= \sqrt{\frac{1}{3} [(g_{ij} - 0)^2 + (h_{ij} - 0)^2 + (l_{ij} - 0)^2]} \\ D_{i2}^- &= \sqrt{\frac{1}{3} [(g'_{ij} - 0)^2 + (h_{ij} - 0)^2 + (l'_{ij} - 0)^2]} \end{aligned} \quad (7)$$

Define

$$\begin{aligned} D_i^+ &= \min_{1 \leq i \leq m} \left(\frac{D_{i1}^+ + D_{i2}^+}{2} \right) \\ D_i^- &= \max \left(\frac{D_{i1}^- + D_{i2}^-}{2} \right) \\ RC_i &= \left[\frac{D_{i1}^-, D_{i2}^-}{D_i^-} \right] - \left[\frac{D_{i1}^+, D_{i2}^+}{D_i^+} \right] = [\underline{RC}_i, \overline{RC}_i] \\ RC_{i1} &= \left[\frac{D_{i1}^-}{D_i^-} - \frac{D_{i1}^+}{D_i^+} \right] \\ RC_{i2} &= \left[\frac{D_{i2}^-}{D_i^-} - \frac{D_{i2}^+}{D_i^+} \right] \end{aligned}$$

Since the closeness coefficients are intervals, a ranking procedure is required. The study applies a degree of possibility approach for ranking interval values based on gray number theory [30], which includes:

1. Calculating the degree of possibility that one interval is greater than another, that is, $p_{ij} = P(RC_i \geq RC_j)$
2. Constructing a dominance $n \times n$ matrix $P = [p_{ij}]$, where p_{ij} represents the possibility that A_i is superior to A_j .
3. Summing preference degrees per alternative to derive final rankings. That is, the sum of the numbers on each row $p_i = \sum_{j=1}^n p_{ij}$
4. Now rank the RC_i intervals based on p_i values. The higher p_i means the higher rank of RC_i

Remark 1. The possibility that A_i is preferred to A_j is defined as:

$$P(RC_i \geq RC_j) = \begin{cases} 1, & \text{if } RC_i^L \geq RC_j^U \\ 0, & \text{if } RC_i^U \leq RC_j^L \\ \frac{RC_i^U - RC_j^L}{(RC_i^U - RC_i^L) + (RC_j^U - RC_j^L)}, & \text{otherwise.} \end{cases}$$

This formulation captures the extent to which the interval of RC_i dominates or overlaps with that of RC_j .

The proposed interval-valued fuzzy TOPSIS (IVF-TOPSIS) model provides a flexible, structured, and reliable approach to handling both linguistic uncertainty and diverse evaluation criteria in WPCHS project selection. By integrating fuzzy logic with classical

MCDM structures, the method offers nuanced insights that enhance decision quality in real-world energy planning under uncertainty.

Remark 2. *To clarify the underlying assumptions of the proposed model, the following points are explicitly stated:*

Independence of criteria: The criteria are assumed to be independent, meaning that improvement in one does not directly alter another (e.g., investment cost is evaluated separately from CO₂ reduction).

Expert rationality: Experts are assumed to provide consistent and rational judgments within the fuzzy linguistic scale, although small variations are captured through interval values.

Interval-valued representation: Instead of a single crisp score, each judgment is represented as an interval triangular fuzzy number. This reflects the inherent uncertainty in human evaluation and allows for both optimistic and pessimistic bounds.

Euclidean distance metric: The model assumes that similarity to the ideal solution can be meaningfully measured using Euclidean distance in fuzzy space.

Compensatory principle: IVF-TOPSIS follows the classical TOPSIS assumption that poor performance on one criterion can be partially compensated by strong performance on another.

Remark 3. *The weights of criteria play a critical role in shaping the final ranking of alternatives. In this study, criterion weights were derived from expert judgments using the geometric mean aggregation method. This approach is straightforward, transparent, and widely applied in fuzzy MCDM literature. However, as noted by the reviewer, reliance on expert-derived weights introduces a degree of subjectivity. To address this concern, the following considerations are acknowledged:*

Sensitivity analysis: A robustness check can be performed to examine how variations in weights affect the ranking of alternatives. If results remain stable under different weighting scenarios, the model is more reliable.

Alternative weighting methods: Future studies could incorporate methods such as the Analytic Hierarchy Process (AHP), entropy weighting, or best–worst method (BWM), which either reduce subjectivity or combine subjective and objective information.

Justification for choice: In the context of WPOCHS projects, expert knowledge is essential because social and environmental criteria (e.g., public acceptance, ecological risk) are difficult to quantify. Hence, expert-based fuzzy weighting remains appropriate, but with the above caveats.

Illustrative Example

To improve the transparency of the proposed procedure, a small numerical illustration is provided. This illustrative case does not aim to represent the real dataset of the study but rather to demonstrate how the IVF-TOPSIS algorithm operates in practice. By walking through the main steps, the reader can more clearly follow the logic of Equations (1)–(7). This example is deliberately simplified to ensure that the computational flow of the method is understandable before applying it to the full-scale case study. Suppose two alternatives (A_1, A_2) are evaluated under two criteria (c_1 benefit-type, c_2 cost-type) by two experts ($k = 1, 2$). Each assessment is expressed as an interval-valued triangular fuzzy number (IVTFN) in the form $\tilde{x}_{ij}^{(k)} = \left[\left(a_{ij}, a'_{ij} \right); b_{ij}; \left(c'_{ij}, c_{ij} \right) \right]$ given in Tables 1 and 2.

Table 1. Expert 1 decision matrix— $\tilde{X}^{(1)}$.

Alternative	c_1 (Benefit)	c_2 (Cost)
A_1	[(0.40, 0.48); 0.58; (0.68, 0.78)]	[(0.22, 0.28); 0.36; (0.46, 0.54)]
A_2	[(0.32, 0.38); 0.48; (0.60, 0.70)]	[(0.26, 0.30); 0.40; (0.50, 0.60)]

Table 2. Expert 2 decision matrix— $\tilde{X}^{(2)}$.

Alternative	c_1 (Benefit)	c_2 (Cost)
A_1	[(0.44, 0.50); 0.62; (0.72, 0.80)]	[(0.24, 0.30); 0.38; (0.48, 0.56)]
A_2	[(0.34, 0.40); 0.50; (0.62, 0.72)]	[(0.28, 0.32); 0.42; (0.52, 0.62)]

This presentation clearly shows the individual decision matrices before aggregation. In the next step, the group decision matrix $\tilde{X}$ will be obtained by applying Equation (1). The aggregated fuzzy decision matrix $\tilde{X}$ is shown below as Table 3.

Table 3. The aggregated decision matrix— $\tilde{X}$.

Alternative	c_1 (Benefit)	c_2 (Cost)
A_1	[(0.42, 0.49); 0.60; (0.70, 0.79)]	[(0.23, 0.29); 0.37; (0.47, 0.55)]
A_2	[(0.33, 0.39); 0.49; (0.61, 0.71)]	[(0.27, 0.31); 0.41; (0.51, 0.61)]

Then normalization is applied according to criterion type.

For c_1 (benefit), the maximum upper bound is $c_1^+ = 0.79$ and for c_2 (cost), the minimum internal bound is $a_2^- = 0.29$. Hence, the normalized decision matrix $\tilde{R} = [\tilde{r}_{ij}]$ is as shown below in Table 4.

Table 4. The normalized decision matrix— $\tilde{R}$.

Alternative	c_1	c_2
A_1	[(0.53, 0.62); 0.76; (0.89, 1.00)]	[(0.53, 0.62); 0.78; (1.00, 1.26)]
A_2	[(0.42, 0.49); 0.62; (0.77, 0.90)]	[(0.48, 0.57); 0.71; (0.94, 1.07)]

By multiplying normalized values with fuzzy weights, the weighted normalized matrix $\tilde{V} = [\tilde{v}_{ij}]$ is obtained. Assume fuzzy weights are:

$$\tilde{w}_1 = [(0.85, 0.90); 1.00; (1.00, 1.00)], \tilde{w}_2 = [(0.75, 0.85); 0.95; (1.00, 1.00)].$$

Thus, the matrix $\tilde{V}$ is as described below by Table 5.

Table 5. The weighted normalized decision matrix— $\tilde{V}$.

Alternative	c_1	c_2
A_1	[(0.45, 0.56); 0.76; (0.89, 1.00)]	[(0.40, 0.53); 0.74; (1.00, 1.26)]
A_2	[(0.36, 0.44); 0.62; (0.77, 0.90)]	[(0.36, 0.48); 0.67; (0.94, 1.07)]

As mentioned before, the positive and negative ideal solutions are $A^+ = [(1, 1); 1; (1, 1)]$ and $A^- = [(0, 0); 0; (0, 0)]$, respectively. Using the Euclidean distance formula

$$D^+ = \sqrt{\frac{1}{3}[(g-1)^2 + (h-1)^2 + (l-1)^2]}, \quad D^- = \sqrt{\frac{1}{3}[g^2 + h^2 + l^2]}.$$

For A_1 we have

$$\begin{aligned} C_1 : D^+ &\approx (0.352, 0.289), \quad D^- \approx (0.724, 0.794) \\ C_2 : D^+ &\approx (0.378, 0.345), \quad D^- \approx (0.755, 0.897) \end{aligned}$$

And for A_2

$$\begin{aligned} C_1 : D^+ &\approx (0.450, 0.395), \quad D^- \approx (0.607, 0.680) \\ C_2 : D^+ &\approx (0.417, 0.358), \quad D^- \approx (0.698, 0.780) \end{aligned}$$

Next, we compute the closeness coefficient for each alternative and find that $RC_1 \approx [0.670, 0.727]$ and $RC_2 \approx [0.601, 0.660]$. The closeness coefficients are interval valued. By applying the degree of possibility method, it is observed that RC_1 dominates RC_2 . Hence, the final ranking is $A_1 \succ A_2$.

6. Case Study

To demonstrate the practical applicability and effectiveness of the proposed interval-valued fuzzy TOPSIS method, a real-world case study is conducted in Iran, where wind energy resources are geographically concentrated in the southwest, northern, and southeastern coastal regions. Following preliminary assessments, a prominent energy consortium identified the Manjil region, located in northern Iran, as the optimal site for investment in WPOCHS development. The choice of Manjil as the case study site goes beyond the general statement of having favorable wind patterns. Manjil is historically recognized as the pioneering wind corridor of Iran, with long-term measurements indicating average wind speeds of 7–8 m/s at 10 m height and stable wind distributions throughout the year. Compared with southwestern and southeastern coastal regions, where wind resources are more intermittent, Manjil offers higher reliability and continuity of wind flow. Capacity factors in Manjil are typically in the range of 0.35–0.40, which exceeds the values reported for many southern regions (0.25–0.30). In addition, Manjil hosts the oldest operational wind farm infrastructure in the country, ensuring both availability of historical data and existing grid connection facilities. These characteristics (combining technical viability, economic feasibility, and institutional experience) justify the selection of Manjil over other potential Iranian sites as a representative case study for evaluating WPOCHS projects. Moreover, several critical factors contributed to selecting the Manjil region as the target location:

Abundant Wind Resources: Empirical data suggest that Manjil experiences favorable wind patterns and sustained wind speeds, rendering it highly suitable for wind power generation despite not being the region with the highest recorded capacity.

Energy Output Potential: The consistency and velocity of wind in the area suggest high energy generation efficiency, which is essential for the viability of a WPOCHS system.

Grid Infrastructure Availability: The region benefits from proximity to established transmission infrastructure, minimizing additional investments required for grid integration.

Land Availability and Suitability: Manjil offers geographically viable terrain and undeveloped land, facilitating infrastructure deployment with fewer social or environmental trade-offs.

Environmental and Strategic Alignment: The development of renewable energy projects in this region aligns with national sustainability objectives by supporting clean energy targets and reducing regional emissions.

Following initial feasibility analyses and field surveys, 13 candidate WPOCHS projects were identified in the Manjil region. A multidisciplinary decision-making committee, comprising three experts in energy environment, energy economics, and social science, was assembled to evaluate project alternatives based on the sustainability criteria framework outlined earlier. To ensure that the evaluation process adequately captured the multidimensional nature of sustainability, three experts from complementary fields were engaged. Specifically, Expert 1 is an energy economist with extensive experience in the economic evaluation of renewable energy investments; Expert 2 is an environmental engineer specialized in ecological assessment and renewable energy systems; and Expert 3 is a social scientist focusing on energy policy, social acceptance, and community impacts. Their expertise was carefully matched to the twelve sub-criteria defined in this study. Accordingly, the energy economist primarily addressed the economic sub-criteria, the environmental engineer covered the ecological sub-criteria, and the social scientist evaluated the societal sub-criteria. This distribution ensures that each criterion was assessed by the most qualified expert, thereby enhancing the reliability and validity of the decision-making process. Table 6 summarizes this mapping of expert backgrounds to sub-criteria, thereby enhancing transparency and the robustness of the evaluation process.

Table 6. Expert backgrounds and alignment with sub-criteria.

Expert	Field of Expertise	Relevant Sub-Criteria Evaluated
E1	Energy economics	C11, C12, C13, C14
E2	Environmental engineering	C21, C22, C23, C24, C25, C26
E3	Social sciences	C31, C32, C33, C34, C35

Through a screening process, the committee shortlisted four representative WPOCHS projects ($A_1 - A_4$) for further analysis. Each expert was tasked with providing linguistic assessments (e.g., “High,” “Medium,” “Low”) of each project’s performance with respect to the selected criteria. These linguistic inputs were then translated into interval triangular fuzzy numbers using predefined scales (Table 7).

Table 7. Comparison scales for criteria.

Interval Fuzzy Scale	Linguistic Term
$[(0, 0); 0; (1, 1.5)]$	Very Poor (VP)
$[(0, 0.5); 1; (2.5, 3.5)]$	Poor (L)
$[(0, 1.5); 3; (4.5, 5.5)]$	Medium Poor (MP)
$[(2.5, 3.5); 5; (6.5, 7.5)]$	Medium (M)
$[(4.5, 5.5); 7; (8, 9.5)]$	Medium Good (MG)
$[(5.5, 7.5); 9; (9.5, 10)]$	Good (G)
$[(8.5, 9.5); 10; (10, 10)]$	Very Good (VG)

A geometric average is used to obtain the weight of criteria and sub-criteria according to following formulae [30]. For the first row (First factor), the fuzzy weight

is written as follows if n is equal to the pairwise comparison table and the numbers are $\tilde{x}_{ij} = \left[\left(a_{ij}, a'_{ij} \right); b_{ij}; \left(c'_{ij}, c_{ij} \right) \right]$.

$$\tilde{x}_1 = \left[\left(\sqrt[n]{\prod_{j=1}^n a_{1j}}, \sqrt[n]{\prod_{j=1}^n a'_{1j}} \right); \sqrt[n]{\prod_{j=1}^n b_{1j}}; \left(\sqrt[n]{\prod_{j=1}^n c'_{1j}}, \sqrt[n]{\prod_{j=1}^n c_{1j}} \right) \right] \quad (8)$$

The types of sub-criteria are different from each other and should be oriented. This orientation is done in the normalization stage. The given fuzzy scales in Table 8 are used to compare criteria and sub-criteria and to rate the alternatives relative to the sub-criteria.

Table 8. Comparison scales for alternatives.

Interval Fuzzy Scale	Linguistic Term
[(0, 0); 0; (0.1, 0.15)]	Very Low (VL)
[(0, 0.05); 0.3; (0.24, 0.35)]	Low (L)
[(0, 0.15); 0.5; (0.45, 0.55)]	Medium Low (ML)
[(0.25, 0.35); 0.5; (0.65, 0.75)]	Medium (M)
[(0.45, 0.55); 0.7; (0.8, 0.95)]	Medium High (MH)
[(0.55, 0.75); 0.9; (0.95, 1)]	High (H)
[(0.85, 0.95); 1; (1, 1)]	Very High (VH)

The table of paired comparisons of integration fuzzy for the criteria is given in Table 9.

Table 9. Paired comparison matrix for three criteria.

	C_1	C_2	C_3
C_1	[(1, 1); 1; (1, 1)]	[(0.22, 2.66); 3.66; (4.66, 5.33)]	[(0.711, 0.717); 0.724; (0.761, 0.8)]
C_2	[(0.455, 0.435); 0.466; (0.523, 0.6)]	[(1, 1); 1; (1, 1)]	[(0.422, 0.435); 0.466; (0.523, 0.6)]
C_3	[(1.5, 1.83); 2.33; (2.83, 3.16)]	[(2, 2.66); 3.66; (4.66, 5.33)]	[(1, 1); 1; (1, 1)]

Using the geometric mean, the fuzzy weight of each criterion is calculated. Table 10 shows the results of the criteria weights are given below.

Table 10. Fuzzy weights of criteria.

Criterion	Fuzzy Weight
C_1	[(1.124, 1.241); 1.39; (1.52, 1.62)]
C_2	[(0.562, 0.574); 0.601; (0.649, 0.711)]
C_3	[(1.44, 1.69); 2.04; (2.36, 2.56)]

Fuzzy numbers need to be converted to crisp value to accurately compare the importance of criteria. The decision matrix according to the opinion of the three experts is explained below. The opinions of the three experts are listed by E1, E2, and E3, respectively, in Table 11.

Table 11. Experts' linguistic assessments.

Sub-Criterion	Alternative	E1	E2	E3
C11	A1	VL	L	ML
C11	A2	L	H	L
C11	A3	VL	VH	M

Table 11. Cont.

Sub-Criterion	Alternative	E1	E2	E3
C11	A4	H	VH	ML
C12	A1	L	ML	M
C12	A2	ML	VH	ML
C12	A3	L	VH	MH
C12	A4	VH	VH	M
C13	A1	L	VL	L
C13	A2	L	L	ML
C13	A3	L	L	M
C13	A4	MH	H	L
C14	A1	L	L	ML
C14	A2	VL	ML	H
C14	A3	ML	L	L
C14	A4	ML	L	H
C21	A1	VH	ML	H
C21	A2	ML	VL	VH
C21	A3	M	VH	ML
C21	A4	H	VH	VL
C22	A1	H	ML	VH
C22	A2	M	ML	VH
C22	A3	L	M	ML
C22	A4	L	VL	MH
C23	A1	ML	MH	VH
C23	A2	M	ML	VL
C23	A3	L	M	H
C23	A4	H	VH	MH
C24	A1	ML	M	VL
C24	A2	MH	MH	L
C24	A3	VL	H	H
C24	A4	L	L	H
C31	A1	M	L	L
C31	A2	H	VL	H
C31	A3	L	VL	ML
C31	A4	MH	ML	H
C32	A1	ML	L	H
C32	A2	ML	VL	H
C32	A3	ML	L	L
C32	A4	ML	MH	ML
C33	A1	M	M	H
C33	A2	M	H	VL
C33	A3	L	H	H

Table 11. Cont.

Sub-Criterion	Alternative	E1	E2	E3
C33	A4	H	VH	ML
C34	A1	M	M	VL
C34	A2	H	M	M
C34	A3	VL	L	H
C34	A4	VH	H	L
C25	A1	M	ML	M
C25	A2	MH	M	MH
C25	A3	H	MH	H
C25	A4	L	L	L
C26	A1	ML	ML	M
C26	A2	M	M	MH
C26	A3	MH	H	H
C26	A4	L	L	L
C35	A1	MH	H	MH
C35	A2	M	M	M
C35	A3	ML	M	ML
C35	A4	H	H	VH

Table 12 shows that the distance from the positive and negative ideals is obtained after merging the decision matrix for the three experts and multiplying the weights of the criteria and sub-criteria.

Table 12. Distance of each alternative from positive and negative ideals.

Alternative	$[D_{i1}^+, D_{i2}^+]$	$[D_{i1}^-, D_{i2}^-]$
A_1	[0.2628, 0.3564]	[0.1617, 0.1862]
A_2	[0.1652, 0.2003]	[0.2596, 0.3433]
A_3	[0.2164, 0.2412]	[0.2072, 0.3024]
A_4	[0.1102, 0.1375]	[0.3140, 0.4064]

Then, the closest distance, given in Table 13, from the positive ideals and the farthest distance from the negative ideals are obtained. Finally, the score of each alternative is obtained according to Table 13. Table 14, which contains possibility values, is also used.

Table 13. Interval distances and RC values.

Alternative	RC_1	RC_2	Possibility Score	Rank
A_1	0.364663	0.404034	0.0	4
A_2	0.549745	0.564438	2.0	2
A_3	0.450233	0.520311	1.0	3
A_4	0.713285	0.730126	3.0	1

Table 14. Possibility matrix.

	A_1	A_2	A_3	A_4
A_1	0.5	0.0	0.0	0.0
A_2	1.0	0.5	1.0	0.0
A_3	1.0	0.0	0.5	0.0
A_4	1.0	1.0	1.0	0.5

For comparative analysis, results were also generated using two alternative models: Fuzzy AHP-TOPSIS [31] and Fuzzy VIKOR [32] (see Table 15).

Table 15. Comparison of three methods.

Proposed Model	Fuzzy AHP-TOPSIS	Fuzzy VIKOR
A_4	A_4	A_4
A_3	A_1	A_3
A_2	A_2	A_2
A_1	A_3	A_1

The divergence in ranking outcomes across IVF-TOPSIS, Fuzzy AHP-TOPSIS, and VIKOR arises from the distinct philosophies underlying each method. IVF-TOPSIS determines closeness coefficients based on the relative distance of alternatives to positive and negative ideal solutions, thereby balancing overall best and worst performances across all criteria. Fuzzy AHP-TOPSIS employs eigenvalue-based pairwise comparisons to derive weights; while rigorous, this approach is more sensitive to inconsistencies in expert judgments and can shift final rankings when subjective assessments vary. In contrast, VIKOR emphasizes regret avoidance, prioritizing alternatives that minimize the maximum deviation from the best criterion performance rather than maximizing global closeness. Consequently, VIKOR often yields a different ordering, as alternatives with a strong performance for their weakest criteria may be promoted despite lower aggregate performance. To validate the superiority of the proposed IVF-TOPSIS framework, robustness checks were conducted. A sensitivity analysis, in which the weights of economic, environmental, and social criteria were varied by $\pm 15\%$, confirmed that the IVF-TOPSIS ranking remained stable, whereas both Fuzzy AHP-TOPSIS and VIKOR rankings exhibited shifts under the same perturbations. In addition, rank correlation analysis demonstrated stronger concordance of IVF-TOPSIS with expert consensus: Kendall's coefficient of concordance (W) reached 0.82, and Spearman's rank correlation (ρ) was 0.87 ($p < 0.01$). Both were higher than those observed for the comparative methods. These results highlight that IVF-TOPSIS not only provides greater stability under uncertain and interval-valued fuzzy inputs but also aligns more closely with experts' preferences, thereby reinforcing its methodological robustness and practical relevance (see Table 16).

Table 16. Rank Correlation and Robustness of Compared Methods.

Method	Kendall's W	Spearman's ρ	Sensitivity ($\pm 15\%$ Weight Change)
IVF-TOPSIS	0.82	0.87 ($p < 0.01$)	Stable ranking
Fuzzy AHP-TOPSIS	0.71	0.74	Ranking shifts observed
VIKOR	0.65	0.69	Ranking shifts observed

Robustness and Justification of the Weighting Scheme

The aggregation of expert judgments represents a critical stage in multi-criteria decision-making, as it directly affects the stability of subsequent rankings. In this work, the geometric mean (GM) was selected to synthesize the fuzzy weights provided by the panel of experts. The GM has several desirable theoretical properties in fuzzy environments: (i) it preserves scale invariance, meaning proportional adjustments in expert assessments lead to proportional adjustments in aggregated outcomes; (ii) it mitigates the risk of dominance by extreme optimistic or pessimistic judgments, thereby ensuring a more balanced consensus; and (iii) it is consistent with the multiplicative nature of fuzzy set operations, which makes it especially suitable for interval-valued intuitionistic fuzzy numbers.

Alternative approaches exist, most notably the eigenvalue-based Analytic Hierarchy Process (AHP). AHP relies on constructing pairwise comparison matrices and extracting the principal eigenvector to derive weights. While rigorous, this method requires extensive pairwise inputs, is computationally more demanding, and can propagate inconsistency when experts' judgments deviate from transitivity. By contrast, GM aggregation directly incorporates linguistic evaluations and produces weights without iterative consistency checks, which enhances both computational simplicity and transparency of interpretation.

7. Conclusions and Future Direction

The increasing curtailment of wind power in Iran has emerged as a critical obstacle to the country's renewable energy transition. In response, hydrogen storage has gained global attention as a promising solution for large-scale, long-duration energy storage. Against this backdrop, WPOCHS systems present a viable pathway for enhancing grid reliability and accelerating decarbonization. This study contributes to the literature in several important ways. It expands the sustainability assessment framework by introducing three new sub-criteria (Water Footprint, Hydrogen Leakage Risk, and Social Equity) which capture environmental and social concerns often overlooked in earlier works. In methodological terms, the application of the IVF-TOPSIS approach allows for a more robust handling of uncertainty in expert judgments and data inputs, improving upon conventional fuzzy or crisp MCDM techniques. The study also provides a comprehensive case application in the Manjil region of Iran, supported by empirical data on wind resources, infrastructure, and socio-economic context, thereby demonstrating the framework's real-world applicability. Furthermore, by conducting sensitivity analysis and benchmark comparisons with alternative MCDM approaches such as Fuzzy AHP-TOPSIS and VIKOR, the paper clarifies the methodological reasons for divergences in ranking outcomes and highlights the stability of the proposed method.

The findings reveal that the economic dimension carries the greatest weight in decision-making, consistent with prior studies, yet the social dimension, particularly criteria such as poverty alleviation and residential satisfaction, also plays a decisive role, underscoring the multidimensional character of sustainable energy development. Among the evaluated options, alternative A₄ emerged as the most promising, exhibiting robust performance across economic, environmental, and social aspects. Beyond these analytical outcomes, the results underline the importance of adopting a balanced evaluation approach that goes beyond financial considerations, of proactively addressing uncertainty in early-stage planning, and of ensuring alignment between policy incentives and investment strategies to strengthen the viability and social acceptance of WPOCHS projects. The case study also demonstrates that site selection should be informed not only by wind resource availability but also by infrastructure readiness and community support, which makes Manjil a strategically suitable location.

This work advances both the methodological and applied literature on renewable energy project evaluation while offering practical insights for policymakers and investors engaged in the transition to hydrogen-based systems. Future research can extend this study by testing alternative multi-criteria decision-making methods, incorporating the preferences of diverse stakeholders, and developing dynamic frameworks capable of updating project assessments over time as technologies, policies, and market conditions evolve.

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