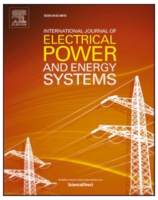
Electrical Power and Energy Systems 177 (2026) 111835

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes



Dynamic expert project assessment for green wind energy park investments via molecular fuzzy reinforcement learning decision-making technique

Gang Kou [a,h], Serhat Yüksel [b,c], Hasan Dinçer [b,c,d,f], Merve Acar [b,*], Serkan Eti [e,g], Ümit Hacıoğlu [d]

[a] School of Business Administration, Faculty of Business Administration, Southwestern University of Finance and Economics, Chengdu 611130, China
[b] School of Business, Istanbul Medipol University, Istanbul, Turkey
[c] Department of Economics and Management, Khazar University, Baku, Azerbaijan
[d] School of Business, Ibn Haldun University, Istanbul, Turkey
[e] IMU Vocational School, İstanbul Medipol University, İstanbul, Turkey
[f] University College, Korea University, Republic of Korea
[g] ARUCAD Research Centre, Arkin University of Creative Arts and Design, Northern Cyprus, Mersin 10, Turkey
[h] School of Digital Media Engineering and Humanities, Hunan University of Technology and Business, Changsha 410205, China

ARTICLE INFO

Keywords:
Wind energy parks
Green energy
Energy investments
Dynamic expert evaluations
Fuzzy decision-making

ABSTRACT

Wind energy parks play a key role in sustainable energy production and carbon emission reduction. This study proposes a novel decision-making framework to identify effective investment strategies for green wind energy park projects. A dynamic expert dataset is constructed using the Q learning algorithm, while molecular fuzzy Bayesian network and molecular fuzzy multi objective particle swarm optimization are used to weight evaluation criteria and rank strategy alternatives. The analysis focuses on a 50 MW onshore wind farm with an average wind speed of 7.7 m/s and an annual energy production of approximately 153 GWh. The project provides an annual carbon reduction of nearly 95,000 tons and demonstrates strong operational efficiency. The findings show that social compliance and ecological compliance are the most critical evaluation criteria, while balanced energy supply with energy storage integration emerges as the most effective investment strategy.

1. Introduction

Green wind energy parks refer to facilities where environmental impacts are minimized while wind energy is being produced. Therefore, these projects are designed with a focus on sustainability. Wind energy is recognized as environmentally friendly because it does not cause carbon emissions. In these parks, it is aimed to produce wind energy in a sustainable and environmentally friendly way [57]. Energy production facilities where such large-scale turbines are located together are also defined as green wind energy parks. It is possible to talk about many advantages of these projects. Because there are no carbon emissions during the energy production process, climate change can be combated much more successfully [13]. Energy production capacity can be high by systematically placing more than one wind turbine. Owing to this action, it can be much easier to achieve energy independence in the country [25]. Driven by increasing concerns about climate change and global warming, the global renewable energy market has experienced significant growth in recent years. The global installed capacity of renewable energy increased by approximately 50% in 2024, reflecting the accelerating transition toward sustainable energy systems. By the end of 2024, the total global installed capacity of renewable energy technologies including solar, wind, hydropower, geothermal, marine energy, and biogas reached approximately 4,448.1 GW. Among these sources, wind energy accounted for nearly 1,021 GW of the total installed capacity. This remarkable expansion of renewable energy capacity demonstrates the growing global commitment to reducing carbon emissions and promoting environmentally sustainable energy production Nassar et al. [43]. The rapid development of the renewable energy sector has therefore increased the importance of efficient investment strategies and decision-making frameworks for wind energy park projects.

The increasing concentration of carbon dioxide emissions in the atmosphere has become one of the most critical drivers of the global

---

[*] Corresponding author.

E-mail addresses: kougang@swufe.edu.cn (G. Kou), serhatyuksel@medipol.edu.tr (S. Yüksel), hdincer@medipol.edu.tr (H. Dinçer), merve.acar@medipol.edu.tr (M. Acar), seti@medipol.edu.tr (S. Eti), umit.hacioglu@ihu.edu.tr (Ü. Hacıoğlu).

https://doi.org/10.1016/j.ijepes.2026.111835
Received 6 January 2026; Received in revised form 17 March 2026; Accepted 7 April 2026

energy transition. Fossil fuel-based electricity generation is a major contributor to greenhouse gas emissions and climate change. Therefore, reducing CO_2 emissions has become a central objective of energy policies worldwide. Renewable energy technologies, particularly wind energy, play a crucial role in achieving this objective by generating electricity without direct carbon emissions during operation. The expansion of wind energy capacity significantly contributes to lowering the carbon intensity of electricity production and supports international climate targets. Consequently, the development of efficient wind energy park investments has become an important strategy for promoting cleaner energy systems and reducing the environmental impact of electricity generation. The global energy system has been undergoing a significant transformation due to increasing energy demand, climate change concerns, and the need to reduce greenhouse gas emissions. Renewable energy sources have become a critical component of sustainable energy policies across many countries. Among these sources, wind energy has emerged as one of the fastest growing technologies because of its high scalability, environmental benefits, and relatively low operational costs [51], Saleem and Abas [52],c). Many governments and private investors are therefore increasing their investments in wind energy infrastructure to achieve long term energy security and sustainability targets [26]. However, wind energy park investments involve complex decision-making processes that require the evaluation of multiple economic, environmental, operational, and social factors simultaneously. This complexity creates significant challenges for investors and policymakers when determining the most appropriate strategies for improving the performance and sustainability of wind energy projects [14].

There are some variables that are important for the performance of green wind energy park investments. Financial feasibility is vital to improving the performance of these parks. Thanks to this analysis, the economic viability of an investment is evaluated El-Khozondar et al. [22]. In this process, the total costs and potential revenues of the project are analyzed. Ensuring the operational performance of businesses is also an important issue in this process [30]. Efficient operational processes both increase energy production and support the economic sustainability of the investment by reducing costs. Ecological harmony is a factor that minimizes the environmental impact of energy parks [36]. This situation also affects the increase in the long-term performance of projects. Social harmony is also a significant factor in this process. Ensuring this harmony increases social acceptance. This condition also contributes to the long-term sustainability of projects Nassar et al. [41].

Wind energy plays an important role in reducing greenhouse gas emissions and supporting the transition toward sustainable energy systems. Compared with fossil fuel-based electricity generation, wind power produces significantly lower carbon emissions and contributes to the mitigation of global warming. In addition, wind energy projects create economic opportunities such as local employment and regional development. However, the expansion of wind farms may also generate certain environmental and social impacts. These impacts may include land use changes, visual impacts on landscapes, noise generation, and potential effects on wildlife habitats, particularly birds and bats [7]. Furthermore, local communities may express concerns regarding landscape alteration and residential quality of life around wind farms. Therefore, evaluating wind energy investments requires a balanced consideration of both environmental benefits and potential social impacts to ensure sustainable and socially acceptable renewable energy development.

The identification of key factors influencing green wind energy park investments is a critical issue for ensuring efficient resource allocation and effective project planning. Determining these factors enables investors and policymakers to allocate limited resources such as capital, labor, and time more efficiently and avoid unnecessary expenditures associated with less significant aspects of the project [50]. When the most influential criteria are clearly defined, potential risks related to technical, financial, environmental, and operational aspects of wind energy projects can be anticipated and managed more effectively. Consequently, decision makers can implement appropriate strategies to mitigate these risks and improve the long-term sustainability of wind energy investments. In addition, focusing on the most critical factors supports both environmental and economic sustainability by improving project efficiency and reducing uncertainties in investment planning [40]. However, despite the growing importance of renewable energy investments, the existing literature provides limited comprehensive frameworks for systematically identifying and prioritizing the most influential factors affecting wind energy park investment decisions. Most studies focus on technical feasibility or financial analysis without providing integrated decision-making models that capture complex uncertainties and dynamic expert evaluations [2],Aqila et al. [8]a,b). Therefore, this limitation represents an important research gap in the literature and highlights the need for advanced analytical frameworks that can effectively evaluate and prioritize the critical factors influencing green wind energy park investments.

The aim of this study is to identify appropriate investment strategies to increase the effectiveness of the green wind energy parks projects. Within this regard, a novel decision-making model has been established. Firstly, dynamic expert dataset is constructed by the help of Q-learning algorithm. In this process, reward and penalty degrees are computed, and average values are estimated. Moreover, performance indicators are weighted via molecular fuzzy (MF) Bayesian network (BANEW). For this purpose, angles are obtained, and reciprocal values are calculated. In this scope, decision matrix is weighted, and global best positions are determined. In summary, following two research questions are created.

(1) Which performance indicators play the most key role for project evaluation in wind energy park investments?
(2) Which strategy alternatives for increasing the efficiency of green wind energy park projects should be prioritized?

The main motivation is to define adequate investment approaches to improve the productivity and efficiency of green wind energy park investments. For these projects to operate with high efficiency, critical performance indicators and appropriate strategies must be clearly defined. However, there is no consensus on these issues in the literature. Failure to clearly define performance indicators may lead to inefficient use of resources. Similar to this situation, failure to implement the right strategies may increase the risk of project failure. This situation increases the uncertainty in the process and makes investors anxious. To solve these problems, a comprehensive priority analysis must be performed to determine the most important factors. A decision-making model can be established to achieve this goal. For this model to be effective, it is important to prefer innovative fuzzy sets that can reduce uncertainty. Moreover, weighting and ranking techniques appropriate to the purpose of the study must also be selected.

The total significance of this research for the academic literature is that appropriate investment strategies are identified to provide performance improvements for the green wind energy parks by generating a novel decision-making model. Hence, the effectiveness of these investments can be increased. This condition has a powerful contribution to the long-term profitability of these investments. This situation can be accepted as the main theoretical contribution of the study. On the other side, there are also some methodological contributions of this study. The recommended model has certain advantages over previously established models. These significant issues are demonstrated below.

(1) The new decision-making model developed in the study utilizes dynamic expert opinions. In this context, an expert was asked to change the criteria and weights 3 different times with a 3-year interval. In this way, opinions that change over time are obtained. This situation also enables the provision of dynamic expert evaluations. This new application also contributes significantly to the literature. Considering the time-dependent changes

of expert opinions represents an innovative approach that differs from traditional methods. In the literature, expert opinions are usually obtained with one-time evaluations. In this context, it is ignored that these opinions may change over time. Therefore, a literature innovation is introduced by performing a dynamic evaluation in this model. The factors affecting the performance of wind energy projects are particularly sensitive to environmental, technological or economic changes. Considering expert opinions that change over time allows more realistic and adaptable decision-making processes to be obtained. On the other hand, uncertainty can be reduced with different data obtained over time rather than one-time expert opinions. This makes it possible to obtain more accurate analysis results.

(2) Molecular fuzzy numbers provide a wide range of benefits both theoretically and practically. In the literature, fuzzy logic models are generally considered with a fixed mathematical structure. In this model, the use of dynamic and multidimensional properties of molecular geometry increases the effectiveness of the analysis results. Moreover, the use of molecular geometry allows better analysis and management of uncertainty in complex systems such as energy investments. Furthermore, molecular fuzzy numbers can be easily adapted according to changing conditions. This makes the model more flexible and useful compared to classical methods. In other words, enriching decision matrices with geometric properties allows special models to be made for different situations.

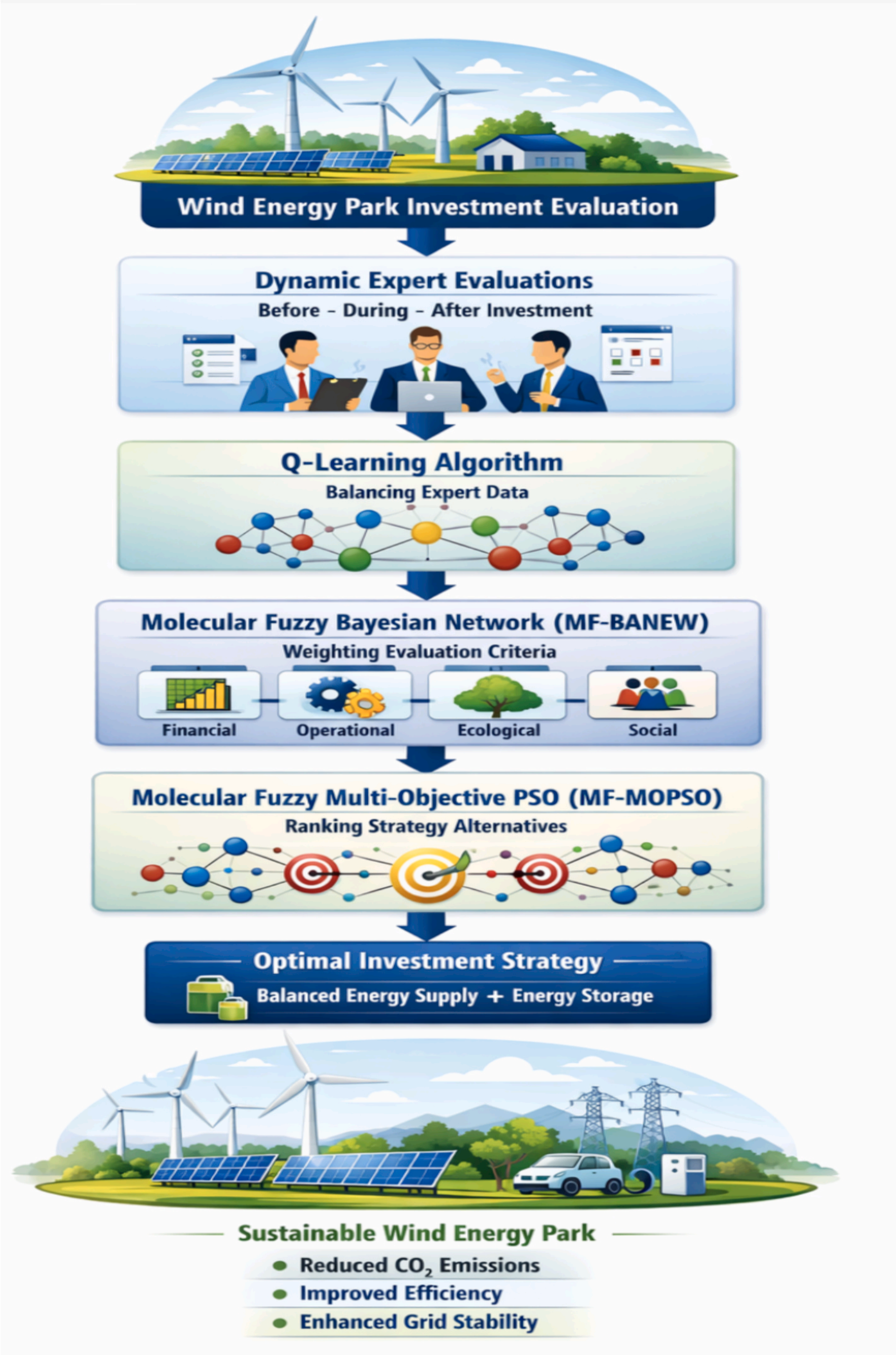


Fig. 1. Graphical Abstract.

(3) In the study, Bayesian network approach is used to calculate the importance weights of the criteria. This model has some advantages compared to other models in the literature. Probability-based evaluations are made in the analysis process of this model. Owing to this condition, it is possible to manage the uncertainty in the process much more effectively. Analytic hierarchy process approach generally calculates the criteria weights based on definite and deterministic data. Since Bayesian network is a probability-based approach, it is much more successful in modeling uncertainties and missing data. Preference ranking organization method for enrichment evaluations technique evaluates the relationships between the criteria independently. Bayesian network is a model that can define conditional dependencies. This situation allows the effect of factors on other criteria to be analyzed directly. Elimination and choice translating reality approach cannot directly analyze the causality relationships between the factors. Bayesian network model can analyze causal directions.

This study provides several important contributions to the literature on renewable energy investment evaluation and decision making under uncertainty. First, the study introduces a dynamic expert evaluation framework by integrating the Q learning algorithm into the decision-making process, allowing expert opinions collected from different time periods to be incorporated into the analysis. This approach improves the realism of the evaluation process compared with traditional models that rely on static expert assessments. Second, the study applies molecular fuzzy sets within a Bayesian network based weighting mechanism, enabling a more effective representation of uncertainty and interdependencies among evaluation criteria. Third, the integration of molecular fuzzy multi objective particle swarm optimization allows the identification of optimal investment strategies under complex decision environments. By combining dynamic learning, advanced uncertainty modeling, and multi objective optimization within a unified framework, the proposed model provides a novel analytical tool for evaluating green wind energy park investments and improving strategic decision making in renewable energy projects. Fig. 1 illustrates the graphical abstract based on the contributions of the manuscript to the literature.

The manuscript has six different sections. The missing part of the literature is underlined in the following section. The third part explains each step of the proposed model. The fourth part includes the results of this model. The final chapters offer information about discussion, future research recommendations and limitations.

2. Literature review

Green wind energy parks reduce the carbon footprint by promoting clean energy production, while also making a significant contribution to sustainable development goals [33]. One of the important criteria in determining the most appropriate strategy for green wind energy investments is financial feasibility Saleem et al. [53,4]. Initial capital, installation cost, operation and maintenance cost, energy production capacity, incentives and financing options are some of the issues evaluated within the scope of financial feasibility [47]. Wang et al. [60], indicated in their study that green finance plays an essential role in directing wind energy projects. They emphasized that wind energy investments realized through green financing will reduce dependence on fossil fuels. In addition, Boadu and Otoo [11] conducted a comprehensive study on the development of wind energy in Africa. In the study, it is stated that investments in wind energy will increase energy production capacity and clean energy production. Similarly, Chen et al. [16] noted that wind energy production costs are decreasing rapidly. This situation increases the potential for wind energy utilization.

Operational performance is one of the effectiveness criteria for raising the efficiency of green wind energy park investments. Wind energy projects with high operational performance minimize fluctuations in energy production, reducing energy costs and increasing the use of renewable energy [24], Santos and González [56]. Indeed, Jung et al. [34] emphasized in their study that technological developments are an important factor for increasing the efficiency of energy produced by wind energy. Similarly, Ba-abbad et al. [9] stated that energy produced using solar and wind energy is an effective way to combat climate change. In addition, Ouerghi et al. [45] mentioned that wind farms can be used to reduce dependence on distant power networks, increase energy security and reduce energy dependence. Finally, Nassar et al. [42] emphasize that wind energy reduces the carbon footprint in the energy cycle. The study also noted that wind energy will be effective in reducing carbon emissions.

The other critical criterion for increasing effectiveness of green wind energy park investments is ecological compatibility. Ensuring ecological compatibility not only ensures environmental sustainability in renewable energy projects [54], but also contributes significantly to the long-term success and social acceptance of investments [5,28]. As an example; Hasheminezhad et al. [32] stated that the use of recycled material in the material used for wind power generation is an innovative sustainable solution. The study also emphasized the importance of waste management in green energy production. In addition, Maimó-Far et al. [37] emphasized that energy distributions should be realized by considering ecological and technical factors. The study draws attention to the energy-land nexus that should be considered in determining the production location for renewable energy sources. Finally, Alshehhi et al. [6] analyzed the factors affecting the acceptance and durability of wind energy. The study highlighted that socioeconomic factors are important in the adoption of wind energy.

Social compliance in green wind energy park investments is one of the important criteria for planning wind energy projects in accordance with the needs, expectations and social structure of the local community. Social acceptance of green wind park projects is also important for sustainable development [59,1]. Indeed, Balotari-Chiebáo and Byholm [10] emphasized in their study that land use regulations for wind energy production should be determined in line with ecological concerns. Ramalho et al. [48] demonstrsted that the location of wind energy systems will have impacts on the habitats of living things. However, Prieto-Herráez et al. [46] emphasized the importance of public acceptance in renewable energy production and especially in wind energy production. The study also emphasizes that this leads to improvements in the profit from the energy sold. Finally, Töller et al. [58] argue that public acceptance is facilitated by holding a referendum on the establishment of wind power generation facilities.

The literature review revealed some important conclusions. Green wind energy park is one of the production methods used in green energy production. These projects have a positive influence on the sustainable development goals. However, these projects include very complex processes. Because of this issue, prior factors of this process should be defined so that effective investment strategies can be implemented. However, the number of such studies in the literature is quite limited. Consequently, to fill this gap, a priority analysis should be done, considering a wide range of variables.

Although previous studies provide valuable insights into wind energy investments and renewable energy project evaluation, several important limitations remain. Many studies primarily focus on technical efficiency, site selection, or financial feasibility by employing conventional multi criteria decision making methods such as AHP, TOPSIS, and PROMETHEE. While these approaches provide structured evaluation frameworks, they generally rely on static expert judgments and deterministic data structures. This limitation may reduce their ability to capture dynamic changes in expert perceptions and evolving technological or environmental conditions. In addition, traditional fuzzy approaches often adopt fixed membership structures, which may not fully represent the complex uncertainty inherent in renewable energy investments. Therefore, there is still a need for decision making frameworks that can integrate dynamic expert assessments and advanced uncertainty modeling techniques. In this context, the integration of Q learning with molecular fuzzy based Bayesian network and multi objective particle swarm optimization provides a more adaptive and flexible analytical framework. This structure enables the analysis of time dependent expert evaluations and improves the reliability of strategic investment decisions for green wind energy park projects. Literature comparison is given in Table A1.

3. Methodology

This study proposes an integrated decision-making framework to evaluate green wind energy park investments by combining dynamic expert assessment with advanced fuzzy based optimization techniques. The proposed framework consists of three main stages. In the first stage, dynamic expert evaluation datasets are generated using the Q learning algorithm in order to balance expert assessments collected at different time periods and to construct a consistent evaluation structure. In the second stage, the importance weights of the evaluation criteria are determined using the molecular fuzzy Bayesian network approach, which allows the modeling of conditional relationships between criteria under uncertainty. In the final stage, the molecular fuzzy multi objective particle swarm optimization method is applied to rank the strategy alternatives and identify the most appropriate investment strategies. This integrated structure enables a dynamic and uncertainty sensitive evaluation process for wind energy park investments.

This paper proposes a molecular fuzzy reinforcement learning decision-making technique using dynamic expert assessment to determine the most appropriate strategy for increasing the efficiency of green wind energy park investments. Within the scope of this proposed methodology, the uncertainty in expert assessments is analyzed with molecular fuzzy sets (MFSs), while the unbalanced evaluations due to the differences in expert evaluations at different times are balanced with the Q-learning algorithm. In addition, the factors for the project assessment in wind energy investments are weighted with the MF-BANEW method, while the strategy alternatives for increasing the efficiency of green wind energy park projects are ranked with MF-MOPSO.

To provide a clearer understanding of the proposed analytical framework, the overall research process can be summarized in a structured sequence of stages. First, dynamic expert evaluations are collected from different time periods of the wind energy investment project. These datasets are then balanced using the Q learning algorithm to generate a consistent dynamic expert dataset. In the second stage, the importance weights of the evaluation criteria are determined using the molecular fuzzy Bayesian network approach, which allows the modeling of interdependencies between the criteria under uncertainty conditions. In the final stage, the molecular fuzzy multi objective particle swarm optimization method is employed to rank the strategy alternatives and determine the most appropriate investment strategies. The final outputs of the framework include the priority levels of performance indicators and the ranking of strategic investment alternatives for improving the efficiency of green wind energy park projects. The flow for dynamic expert project assessment for green wind energy park investments is visually presented by Fig. 2.

Definitions about MFS used for uncertainty analysis are given below [31,21].

Definition 1 Let a set S be a universe of discourse. A MFS $\widetilde{M}$ is an element having the form $\widetilde{M} = \{x, \langle \Phi_{\tilde{M}}(x), \ \Psi_{\tilde{M}}(x), \ \Omega_{\tilde{M}}(x) \rangle | x \in S\}$ where the function $\Phi_{\tilde{M}}(x) = 1 - \frac{\mathfrak{z}_u}{\mathfrak{z}_{max}}$; $\Psi_{\tilde{M}}(x) = \frac{\mathfrak{z}_u}{\mathfrak{z}_{max}}$; $\Omega_{\tilde{M}}(x) = 1 - \left(\left(1 - \frac{\mathfrak{z}_u}{\mathfrak{z}_{max}}\right) + \frac{\mathfrak{z}_u}{\mathfrak{z}_{max}}\right)$ and $\Phi_{\tilde{M}}(x) + \Psi_{\tilde{M}}(x) + \Omega_{\tilde{M}}(x) = 1$ are the degree of membership, non-membership, hesitant of x to $\widetilde{M}$, respectively.

Definition 2: *Let* $\widetilde{M}_1$ *and* $\widetilde{M}_2$ *be two molecular fuzzy numbers* (*MFNs*). *Then, the general operations are presented by Equations* (1)-(5).

$$\widetilde{M}_1 \cdot \widetilde{M}_2 = \left\{ \left(x, \Phi_{\tilde{M}_1}(x) \cdot \Phi_{\tilde{M}_2}(x), \Psi_{\tilde{M}_1}(x) \cdot \Psi_{\tilde{M}_2}(x), \Omega_{\tilde{M}_1}(x) \cdot \Omega_{\tilde{M}_2}(x) \right) | x \in S \right\} \tag{1}$$

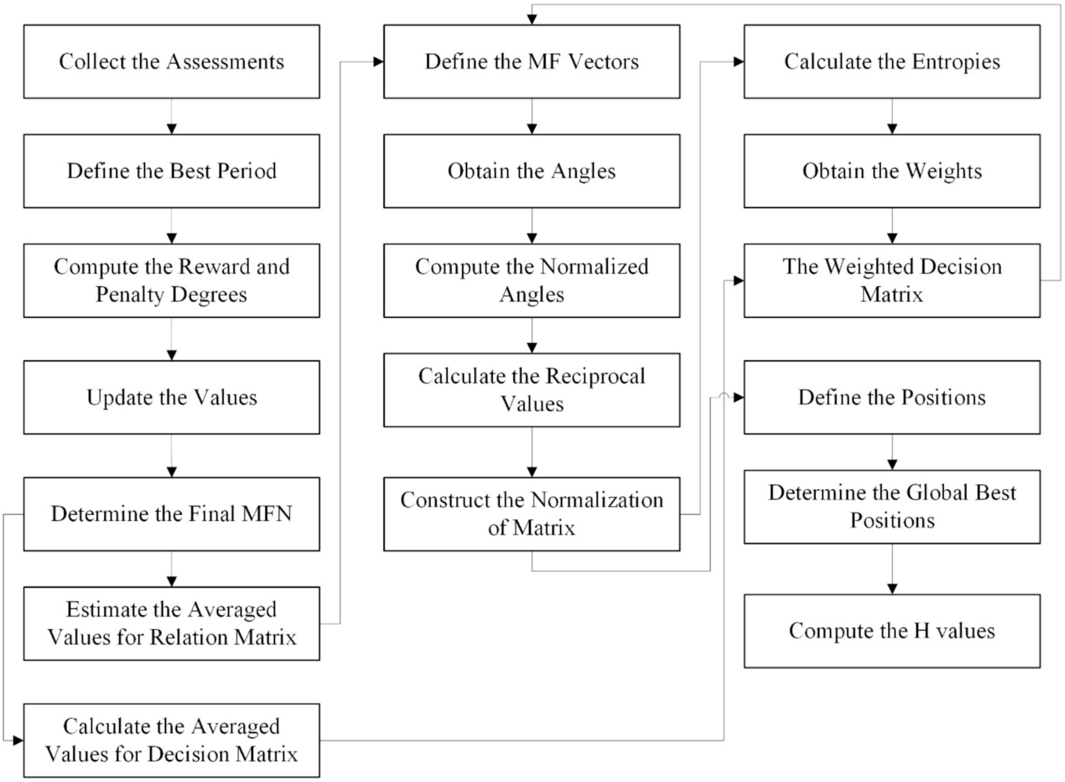


Fig. 2. The flow for dynamic expert project assessment.

$$\lambda\cdot\widetilde{M}_1 = \left\{\left(x, \min\left(\lambda\cdot\Phi_{\widetilde{M}_1}(x), 1\right), \max\left(1-\lambda\left(1-\Psi_{\widetilde{M}_1}(x)\right), 0\right), \max\left(1-\lambda\left(1-\Omega_{\widetilde{M}_1}(x)\right), 0\right)\right) | x\in S\right\} \tag{2}$$

$$\widetilde{M} = \left(\bigcup_{i=1}^{k}\widetilde{M}_i\right) = \left\{\left(x, \frac{1}{k}\sum_{i=1}^{k}\Phi_{\widetilde{M}_i}(x), \frac{1}{k}\sum_{i=1}^{k}\Psi_{\widetilde{M}_i}(x), \frac{1}{k}\sum_{i=1}^{k}\Omega_{\widetilde{M}_i}(x)\right)\middle| x \in S\right\} \tag{3}$$

$$\widetilde{M}_1 \cup \widetilde{M}_2 = \left\{\left(x, \max\left(\Phi_{\widetilde{M}_1}(x), \Phi_{\widetilde{M}_2}(x)\right), \min\left(\Psi_{\widetilde{M}_1}(x), \Psi_{\widetilde{M}_2}(x)\right), \min\left(\Omega_{\widetilde{M}_1}(x), \Omega_{\widetilde{M}_2}(x)\right)\right) | x\in S\right\} \tag{4}$$

$$\widetilde{M}_1 \cap \widetilde{M}_2 = \left\{\left(x, \min\left(\Phi_{\widetilde{M}_1}(x), \Phi_{\widetilde{M}_2}(x)\right), \max\left(\Psi_{\widetilde{M}_1}(x), \Psi_{\widetilde{M}_2}(x)\right), \max\left(\Omega_{\widetilde{M}_1}(x), \Omega_{\widetilde{M}_2}(x)\right)\right) | x\in S\right\} \tag{5}$$

3.1. *Q-learning algorithm*

Q-learning algorithm is a reinforcement learning algorithm that transforms different assessment data sets into balanced data sets according to parameters such as reward (f_c), penalty $\left(f_p\right)$ and learning rate (f_{lr}) factors. Thus, according to the most valuable assessment dataset, other datasets are balanced. The aim of this method is to create optimal values of assessment matrices by maximizing the cumulative reward and minimizing the cumulative penalty. The steps of the Q-learning algorithm are as follows [29]:

The reward and disciplinary degrees among the best period and others are calculated with the help of Eqs. (6) and (7), where the evaluation for the best period $\left(Q_{s,a(bestP)}\right)$ is the baseline Q matrix and the assessments for the other periods are $\left(Q_{s,a(otherP)}\right)$.

$$D_{r_{s,a}} = f_c \times \left(Q_{s,a(bestP)} - Q_{s,a(otherP)}\right) \tag{6}$$

$$D_{p_{s,a}} = f_p \times \left(Q_{s,a(otherP)} - Q_{s,a(bestP)}\right) \tag{7}$$

Afterwards, the updated Q matrix $\left(Q'_{s,a}\right)$ is constructed using f_{lr} with Equation (8).

$$Q'_{s,a} = Q_{s,a(bestP)} + f_{lr} \times \left(D_{r_{s,a}} - D_{p_{s,a}}\right) \tag{8}$$

Equation (9) is used to determine the optimal Q matrix.

$$\max_{s,a}$$

where ε means threshold value for the convergence. As long as the condition in Equation (9) is not met, the Q matrix is updated.

3.2. *Normalization of MFN*

Normalization of *MFN* respect to various molecular geometry shapes is used for comparative of ranking or weighting. The computing of normalization of the *MFN* are summarized below.

First of all, multi-criteria decision matrix is created [31]. The matrix is shown by Equation (10).

$$\widetilde{X} = \left[\widetilde{x}_{ij}\right]_{m\times n} \tag{10}$$

where $\widetilde{X}$ is multi-criteria decision matrix, $\widetilde{x}_{ij}$ means the MF elements of i-row of j-column of $\widetilde{X}$. Later, the molecular fuzzy vectors of $\widetilde{X}$ a re determined for each row with the help of Equation (11).

$$\varphi_i = \left[(\Phi_{i1}, \Psi_{i1}, \Omega_{i1}), (\Phi_{i2}, \Psi_{i2}, \Omega_{i2}), \cdots(\Phi_{it}, \Psi_{it}, \Omega_{it})\right] \tag{11}$$

$$(\varphi_i.\varphi_j) = \sum_{k=1}^{t}\left(\Phi_{i,k}\cdot\Phi_{j,k} + \Psi_{i,k}\cdot\Psi_{j,k} + \Omega_{i,k}\cdot\Omega_{j,k}\right) \tag{12}$$

Afterwards, the corner among the MF-vectors is approximated by Equation (13).

$$\mathfrak{B}_{\varphi_i\cdot\varphi_j} = cos^{-1}\left(\frac{(\varphi_i.\varphi_j)}{\left(\sum_{k=1}^{t}\left(\Phi_{i,k}^2 + \Psi_{i,k}^2 + \Omega_{i,k}^2\right)\right).\left(\sum_{k=1}^{t}\left(\Phi_{j,k}^2 + \Psi_{j,k}^2 + \Omega_{j,k}^2\right)\right)}\right) \tag{13}$$

where cos^{-1} is reverse cosine function. After the corners are obtained, the standardization of the corners is defined based on various molecular geometry shapes. In general, normalized corners are found by divided with the biggest value of the corners. At the same time, the normalized corners are estimated using the radians of the corners of molecular geometry shapes. The computing process is shown in Equation (14).

$$nz\left(\mathfrak{B}_{\varphi_i\cdot\varphi_j}\right) = \begin{cases} \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{\mathfrak{B}_{max}}; general \\ \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{\pi}; linear \\ \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{2\pi/3}; trigonalplanar \\ \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{\pi/2}; tetrahedral \\ \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{2\pi/5}; trigonalbipyramidal \\ \dfrac{\mathfrak{B}_{\varphi_i\cdot\varphi_j}}{\pi/3}; octahedral \end{cases} \tag{14}$$

where, $\mathfrak{B}_{max}$ is the biggest measure of corner. After that, the reciprocals of the $normalize(\mathfrak{B})$ are calculated using Equation (15).

$$rec\left(\mathfrak{B}_{\varphi_i\cdot\varphi_j}\right) = \frac{1}{nz\left(\mathfrak{B}_{\varphi_i\cdot\varphi_j}\right)} \tag{15}$$

Finally, the normalization of *MFN* is identified by Equations (16) and (17).

$$\mathfrak{n}_{ij} = \frac{rec\left(\mathfrak{B}_{\varphi_i\cdot\varphi_j}\right)}{\sum_{j=1}^{n} rec\left(\mathfrak{B}_{\varphi_i\cdot\varphi_j}\right)} \tag{16}$$

$$\mathscr{N} = \left[\mathfrak{n}_{ij}\right] \tag{17}$$

3.3. *MF-BANEW*

BANEW method, which determines the weights of the factors by analyzing the conditional interdependencies between the factors, uses some calculations belonging to data science. More realistic and accurate results are obtained with data science parameters such as conditional probability and information gain. BANEW stages where *MFN* is applied are shown below [19].

First, the degrees of dependence between factors are collected from experts and converted to MFN. After that, Equation (3) is used, and *MF*-relation matrix is created. This matrix is normalized using Eqs. (11)-(17)

by considering it as the matrix presented in Eq. (10), where *m* is equal to *n* and *t* is equal to *n-1*. After the normalized matrix is obtained, the entropies of the factor are calculated by Eqs. (18) and (19).

$$E(F_i) = -\sum P(F_i).In(P(F_i)) \tag{18}$$

$$E(F_i|F_j) = -\sum P(F_j).P(F_i|F_j).In(P(F_i|F_j)) \tag{19}$$

where $E(F_i)$ and $E(F_i|F_j)$ refer to the entropy for i^{th} factor and the conditional entropy indicating the remaining uncertainty about i^{th} factor after knowing j^{th} factor, respectively. $P(F_i)$ means the prior probability of i^{th} factor and equals to 1/n. Similarly, $P(F_i|F_j)$ is conditional probability of i^{th} factor given j^{th} factor. ln is the function of natural logarithm. Finally, the weight values of factors are obtained using Equation (20).

$$W(F_i) = \frac{E(F_k) - E(F_i|F_j)}{\sum_{k=1}^{n}(E(F_k) - E(F_k|F_j))} \tag{20}$$

The optimization structure of the proposed system is designed to identify the most appropriate strategies for improving the efficiency of green wind energy park investments. Within this framework, the system model integrates multiple evaluation criteria including financial feasibility, operational performance, ecological compliance, and social compliance. These criteria represent the key dimensions influencing the sustainability and efficiency of wind energy projects. The configuration of the optimization framework consists of dynamic expert evaluations, molecular fuzzy uncertainty modeling, and multi objective optimization. The objective of the optimization process is to determine the strategy alternative that maximizes the overall performance of the wind energy park project while maintaining environmental and social sustainability. In this process, the decision variables correspond to the strategy alternatives evaluated under the defined criteria. The optimization procedure considers constraints related to technological feasibility, environmental compatibility, and operational efficiency. The molecular fuzzy MOPSO algorithm iteratively searches for optimal solutions by balancing exploration and exploitation in the search space. As a result, the framework identifies the most appropriate strategy alternatives that can improve the overall performance of wind energy park investments under uncertain conditions.

3.4. MF-MOPSO

The MOPSO method, which uses the multi-objective PSO algorithm to rank the options, is one of the many-factors decision-making techniques that also takes into account the interaction between the alternatives. The MOPSO method establishes pareto-optimal solutions and has a unique algorithm that produces balanced results in this search space. MOPSO stages where *MFN* is applied are introduced below [31].

First, linguistic analyses are collected from experts and converted into MFN. After that, Equation (3) is used, and *MF*-decision matrix is created. Then, the values are multiplied by the criteria weights and a weighted decision matrix is created. This matrix is normalized using Eqs. (11)-(17) by considering it as the matrix presented in Equation (10), where *m* means the number of alternatives and *t* is equal to *n*. The normalization of decision matrix refers to the final decision matrix for ranking algorithm. After the final decision matrix is obtained, the particle presentation in Equation (21) is constructed as a vector for the potential solution.

$$X_i = \{x_{i1}, x_{i2}, \cdots, x_{in}\} \tag{21}$$

Afterwards, the updated velocity of each particle is calculated with the help of Eq. (22).

$$V_{ij}(t+1) = \omega V_{ij}(t) + c_1 r_1 (P_{ij}(t) - X_{ij}(t)) + c_2 r_2 \left(P_{gb_j}(t) - X_{ij}(t)\right) \tag{22}$$

where the values of c_i are 1.5 and ω equals to 0.5. $r_i \in [0,1]$. To ensure the transparency and reproducibility of the proposed analytical framework, the parameter settings of the employed algorithms are clearly defined. In the Q learning stage, the learning rate is set to 0.1 and the convergence threshold is determined as 0.02 to control the stability of the iterative updating process. The reward and penalty values are calculated based on the differences between the baseline period and the other evaluation periods. In the molecular fuzzy Bayesian network stage, the prior probability of each criterion is assumed to be equal due to the absence of prior dominance among the factors. In the molecular fuzzy multi objective particle swarm optimization stage, the cognitive and social coefficients are determined as 1.5 and the inertia weight is set to 0.5 in order to balance exploration and exploitation during the search process. These parameter settings allow the proposed framework to achieve stable and consistent optimization results. In addition, $P_{ij}(t)$ means the most optimal position of particle. Similarly, $P_{gb_j}(t)$ is the global best position among the decision alternatives. Thus, the initial velocity $(V_{ij}(1))$ is determined by Equation (23).

$$V_{ij}(1) = 0.1 \times (P_{max_i} - P_{min_i}) \times r \tag{23}$$

where, P_{max_i} means the maximum value. Similarly, P_{min_i} refers to minimum value. Next, the updated position of each particle is estimated with Equation (24).

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{24}$$

The updated position is computed until $\left|P_{gb_j}(t+1) - P_{gb_j}(t)\right| < 0.001$. Finally, the final values for ranking are found with the help of Equation (25).

$$H_j = \frac{1}{n}\sum_{i=1}^{n} P_{ij} \tag{25}$$

3.5. Assumptions, limitations and uncertainties of the proposed framework

The proposed analytical framework is developed under several assumptions to ensure the applicability of the model in evaluating green wind energy park investments. First, the expert evaluations collected from different time periods are assumed to represent consistent and reliable judgments regarding the performance indicators and strategy alternatives. Second, the selected criteria including financial feasibility, operational performance, ecological compliance, and social compliance are assumed to adequately capture the main dimensions influencing wind energy investment performance. Third, the molecular fuzzy representation of expert evaluations is assumed to effectively model uncertainty in decision making environments. Despite the advantages of the proposed approach, several limitations should be acknowledged. The analysis is based on evaluations obtained from a limited number of experts and a specific wind energy project context. Therefore, the generalization of the results to different geographical regions or energy systems may require additional validation. In addition, the model focuses on a specific set of evaluation criteria and strategy alternatives, while other potential factors may also influence wind energy investment decisions. Uncertainty in the results may arise from changes in technological development, policy regulations, and market conditions affecting renewable energy investments. Furthermore, variations in expert judgments and future energy demand conditions may influence the stability of the obtained rankings. Future studies may incorporate larger expert panels, alternative uncertainty modeling techniques, and scenario-based analyses to further improve the robustness of the decision-making framework.

3.6. Reproducibility, reinforcement-learning formulation and benchmark design

For reproducibility, the linguistic-to-molecular-fuzzy conversion used throughout the study is fixed as H = (0.95, 0.05, 0.00), M = (0.80, 0.15, 0.05), and S = (0.60, 0.30, 0.10). Appendix Table A2 reports this mapping together with an end-to-end worked example.

The Q-learning stage is modeled as a finite Markov decision process. The state $s_p^{(k)}$ is the MF relation or decision matrix of period p at iteration k; the action set A={reward-adjust, penalty-adjust, keep} shifts each entry toward the highest-priority baseline period; the immediate reward is defined as $r_p^{(k)} = -|Q_p^{(k+1)} - Q_{\text{best}}|_1$.

So that lower discrepancy produces larger reward; the state transition is deterministic through the update equation; and the episode terminates when $\max\left|Q^{(k+1)} - Q^{(k)}\right| < \varepsilon$. Because the environment is fixed and the state space is small, the learning block acts as a temporal balancing controller rather than an open-ended online exploration agent.

The best period is selected by the normalized feasibility weights in Table 4. The pre-investment period is used as the baseline because it has the highest composite weight (0.343), slightly above the after-investment period (0.338) and the during-installation period (0.319). This choice minimizes temporal inconsistency while preserving the most information-rich evaluation matrix.

To clarify the role of MF-MOPSO, the particle position is explicitly defined as $x = [x_1, x_2, x_3, x_4, x_5]$ over the five strategy alternatives, subject to $x_i \in [0,1]$ and $\sum_{i=1}^{5} x_i = 1$. The ranking stage simultaneously maximizes the global performance score H, minimizes imbalance among criterion satisfactions, and maximizes the pairwise dominance margin between alternatives. The final ranking is obtained by descending alternative-specific H values. To test robustness rather than only internal consistency, TOPSIS, VIKOR, and PROMETHEE II are additionally used as benchmark baselines under the same crisp score transformation. Appendix Tables A3–A5 summarize the MDP elements, the entropy-based weight derivation, and the benchmark design so that the entire pipeline can be replicated from linguistic inputs to final rankings.

4. Analysis

In this study, the wind energy system considered for the project evaluation is based on a modern horizontal axis wind turbine configuration, which is the most widely used technology in large scale onshore wind farms. Horizontal axis wind turbines are preferred because of their high energy conversion efficiency, technological maturity, and strong reliability under varying wind conditions. The evaluated wind farm project has a total installed capacity of 50 MW, which is achieved through multiple utility scale wind turbines operating within the same wind park. The selected turbine type typically operates with a rotor diameter of approximately 120 to 150 m and a hub height ranging between 90 and 120 m, allowing the system to capture stronger and more stable wind flows. The cut in wind speed of the turbine is around 3 to 4 m/s, while the rated wind speed is approximately 12 to 13 m/s and the cut out wind speed is about 25 m/s. These characteristics allow the turbine system to operate efficiently within the average wind speed conditions observed in the analyzed wind energy project.

Financial feasibility (FF), operational performance (OP), ecological compliance (EC), social compliance (SC) are the factors selected for project evaluation in wind energy investments. Smart turbine control systems for the optimization (STCS), predictive analysis for timely maintenance (PA), balanced energy supply with energy storage integration (BES), real-time grid demand using smart technologies (RGD), shared infrastructure with combined renewable projects (SI) are strategy alternatives for increasing the efficiency of green wind energy park projects. For the feasibility assessment of green wind energy park projects, an expert collects evaluations from three different time periods. This expert has been working in project management and renewable energy investments for more than 25 years. The expert's evaluations are collected 1 year before the investment, at the time of project installation and 1 year after the investment installation and analyzed. The project evaluated in the study has a capacity of 50 MW and its system is an onshore wind farm.

The physical system model used in this study represents a typical onshore wind energy park designed for utility scale electricity generation. The evaluated wind farm has a total installed capacity of 50 MW and operates under average wind speed conditions of approximately 7.7 m/s. The annual energy production of the system is estimated to be around 153 GWh, while the operational efficiency of the wind farm is approximately 95–96%. The system also provides an estimated annual carbon emission reduction of about 95,000 tons of CO_2 compared with conventional fossil fuel-based electricity generation. The capacity factor of the wind farm is approximately 34–35%, which reflects the realistic operational performance of modern onshore wind energy projects. These parameters provide the physical basis of the system model and allow the proposed decision-making framework to evaluate wind energy investment strategies under realistic operational conditions.

To strengthen the physical representation of the wind energy layer, the wind speed at turbine hub height is additionally modeled as $V_{(Z,t)} = V_{(0,t)}(h_Z/h_0)^a$, where $h_0 = 10m$, $h_Z = 100m$, and $alpha = 0.14$. For the case study, the corresponding reference-level wind speed is approximately 5.58 m/s, which yields the observed hub-height average of 7.7 m/s. The turbine power curve is then represented by the standard piecewise function: $E_{(W,t)} = 0, V_{(Z,t)} \leq V_{(cut-in)} or V_{(Z,t)} > V_{(cut-off)}$; $E_{(W,t)} = P_{(rat)}\left(V_{(Z,t)} - V_{(cut-in)}\right)/\left(V_{(rat)} - V_{(cut-in)}\right)$, $V_{(cut-in)} < V_{(Z,t)} < V_{(rat)}$; and $E_{(W,t)} = P_{(rat)}$, $V_{(rat)} \leq V_{(Z,t)} \leq V_{(cut-off)}$, with $V_{(cut-in)} = 3m/s$, $V_{(rat)} = 12m/s$, and $V_{(cut-off)} = 25m/s$. Because annual energy depends on the full wind-speed distribution rather than the average speed alone, the measured annual energy output of 153 GWh is retained as the benchmark economic input while the added power-curve model provides the physical linkage between wind conditions and energy yield.

Eco-environmental performance is also incorporated and the avoided carbon-damage cost is computed by $C_{(CO2)} = EF_{(CO2)} x E_t x phi_{(CO2)}$, where the project-specific emission factor is calibrated as $EF_{(CO2)} = (95{,}000 ton)/(153 GWh) = 0.62 kgCO_2/kWh$ and the social cost of carbon is set to $70/(tonCO_2)$. Eco-adjusted LCOE is then calculated as $LCOE = \left(a(r,n) x C + C_{(O\&M)} - C_{(CO2)}\right)/E_t$ and $PBTM = C/Income$, where $a(r,n)$ is the capital recovery factor.

Because the empirical core of the study is based on one expert and one 50 MW project, a structured perturbation protocol is introduced instead of over-claiming external validity. In the revised robustness analysis, expert-derived criterion scores are perturbed stochastically, criteria weights are varied by plus/minus 10%, and the resulting rankings are re-evaluated over 200 scenarios to test the stability of the decision rather than to fabricate additional field evidence.

4.1. Defining the dynamic expert dataset

The assessments are collected from the expert in three different time periods. Table 1 includes the assessments regarding the factors.

At similar times, assessments are collected from the same expert for strategy alternatives. Table 2 presents the expert's assessments regarding strategy alternatives.

Later, the period with the best assessment needs to be determined. In this context, a feasibility analysis for three periods is performed. Table 3 summarizes the details of the feasibility analysis for the periods.

To determine the best period, the values in Table 3 are normalized by dividing the associated column by the maximum value. The weights of the periods are obtained by normalizing the average values. Accordingly, the most important period is the pre-investment period. The weight values of other periods are shown in Table 4.

The weights in Table 4 are used as f_c and f_p. The weight of the pre-

Table 1
Linguistic assessments about factors.

Before Investment	FF	OP	EC	SC
FF		H	S	S
OP	H		S	S
EC	M	S		H
SC	M	S	S	
During Installation	**FF**	**OP**	**EC**	**SC**
FF		S	H	S
OP	S		S	H
EC	S	S		H
SC	M	S	S	
After Investment	**FF**	**OP**	**EC**	**SC**
FF		M	S	S
OP	M		H	H
EC	M	S		H
SC	M	S	H	

Table 2
The linguistic assessments about strategy alternatives.

Before Investment	**FF**	**OP**	**EC**	**SC**
STCS	H	H	H	S
PA	S	M	H	S
BES	H	S	M	H
RGD	M	M	H	H
SI	S	M	S	H
During Installation	**FF**	**OP**	**EC**	**SC**
STCS	S	H	H	S
PA	S	S	H	S
BES	S	S	M	S
RGD	S	M	H	H
SI	S	M	S	H
After Investment	**FF**	**OP**	**EC**	**SC**
STCS	H	M	M	S
PA	S	M	H	S
BES	M	S	M	H
RGD	M	S	S	S
SI	S	M	S	S

investment period is the f_p, while the weights of other periods are the f_c. Then, the linguistic terms in Table 1 and Table 2 are transformed into MFN by following Equations (1)-(5). Then, Equation (6) is used to compute the $D_{r_{s,a}}$ for relation and decision matrices, while Equation (7) is used to calculate the $D_{p_{s,a}}$ for these matrices. Table 5 presents the $D_{r_{s,a}}$ for the decision matrix.

Similarly, Table 6 presents the $D_{p_{s,a}}$ of the decision matrix.

After computing these two degrees, Equation (8) calculates the $Q'_{s,a}$. The f_{lr} in this equation is 0.1 and Table 7 shows the updated values of the decision matrix.

The convergence condition specified in Equation (9) is tested. Absolute differences are calculated for the first iteration. The values are updated until the absolute differences are less than 0.02. The number of iterations for the correlation and decision matrices is four. As a result of the Q-learning algorithm, the evaluations for the calculated relation matrix are given in Table 8.

Similarly, the values are given in Table 9.

4.2. Normalization of matrices

Equation (14) calculates the averaged MFNs for the relation and

Table 5
$D_{r_{s,a}}$ Of mf-q decision matrix among the dynamic expert periods.

Before Investment-During Installation	FF	OP	EC	SC
STCS	(−0.05, 0.03, 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
PA	(0.00, 0.00, 0.00)	(0.06, −0.05, −0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
BES	(−0.05, 0.03, 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(−0.05, 0.03, 0.02)
RGD	(0.06, −0.05, −0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
SI	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
Before Investment-After Investment	**FF**	**OP**	**EC**	**SC**
STCS	(0.00, 0.00, 0.00)	(−0.12, 0.08, 0.03)	(−0.12, 0.08, 0.03)	(0.00, 0.00, 0.00)
PA	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
BES	(−0.12, 0.08, 0.03)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
RGD	(0.00, 0.00, 0.00)	(0.07, −0.05, −0.02)	(−0.05, 0.03, 0.02)	(−0.05, 0.03, 0.02)
SI	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(−0.05, 0.03, 0.02)

Table 3
Details of feasibility analysis.

	Average Wind Speed (m/S)	Annual Energy Output (GWh/year)	Revenue (Million $/year)	IRR (%)	NPV (Million $)	Operational efficiency (%)	CO2 Reduction (tons/year)	Capacity factor (%)
Before Investment	7.7	153	8.43	10.5	25	96	95,000	35
During Installation	7.5	151	8.43	8.2	18	96	95,000	34
After Investment	7.6	151	8.41	10.2	24	95	94,500	34.5

Table 4
The weights of the period.

	Average Wind Speed (m/S)	Annual Energy Output (GWh/year)	Revenue (Million $/year)	IRR (%)	NPV (Million $)	Operational efficiency (%)	CO2 Reduction (tons/year)	Capacity factor (%)	Average scores	Weights
Before Investment	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.343
During Installation	0.97	0.98	1.00	0.78	0.72	1.00	1.00	0.97	0.93	0.319
After Investment	0.99	0.98	1.00	0.97	0.96	0.99	0.99	0.99	0.98	0.338

Table 6
$D_{p_{s,a}}$ Of mf-q decision matrix among the dynamic expert periods.

Before Investment-During Installation	FF	OP	EC	SC
STCS	(0.05, −0.03, −0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
PA	(0.00, 0.00, 0.00)	(−0.07, 0.05, 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
BES	(0.05, −0.03, −0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.05, −0.03, −0.02)
RGD	(−0.07, 0.05, 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
SI	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
Before Investment-After Investment	**FF**	**OP**	**EC**	**SC**
STCS	(0.00, 0.00, 0.00)	(0.12, −0.09, −0.03)	(0.12, −0.09, −0.03)	(0.00, 0.00, 0.00)
PA	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
BES	(0.12, −0.09, −0.03)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
RGD	(0.00, 0.00, 0.00)	(−0.07, 0.05, 0.02)	(0.05, −0.03, −0.02)	(0.05, −0.03, −0.02)
SI	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.05, −0.03, −0.02)

Table 7
Updated MF-Q decision matrix.

Before Investment-During Installation	FF	OP	EC	SC
STCS	(0.94, 0.06, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.61, 0.29, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.94, 0.06, 0.00)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.94, 0.06, 0.00)
RGD	(0.61, 0.29, 0.10)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)
Before Investment-After Investment	**FF**	**OP**	**EC**	**SC**
STCS	(0.95, 0.05, 0.00)	(0.93, 0.07, 0.01)	(0.93, 0.07, 0.01)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.93, 0.07, 0.01)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)
RGD	(0.60, 0.30, 0.10)	(0.61, 0.29, 0.10)	(0.94, 0.06, 0.00)	(0.94, 0.06, 0.00)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.94, 0.06, 0.00)

decision matrices formed by Equation (10). Table 10 shows the average values.

Similarly, Table 11 also presents the average values for the decision matrix. Table 12..

Then, Equation (11) defines the φ_i. While the t value for the relation matrix is 3, it is 4 for the decision matrix.

After the φ are obtained, Equation (12) presents the $\left(\varphi_i \cdot \varphi_j\right)$ result. Then, Eq. (13) determines the $\mathfrak{B}_{\varphi_i \cdot \varphi_j}$ for the matrix. Equation (14) obtains the $nz\left(\mathfrak{B}_{\varphi_i \cdot \varphi_j}\right)$ according to the molecular geometry shapes. Equation (15) calculates the $rec\left(\mathfrak{B}_{\varphi_i \cdot \varphi_j}\right)$. Finally, Eqs. (16) and (17) estimate the $\mathfrak{n}_{ij}$ of the relation matrix. Accordingly, the $\mathfrak{n}_{ij}$ for the relation matrix

Table 8
The MF-Q values for relation matrix.

Before Investment (initial Q matrix)	FF	OP	EC	SC
FF	(0.00, 0.00, 0.00)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
OP	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
EC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.95, 0.05, 0.00)
SC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)
During Installation (Balanced Q matrix)	**FF**	**OP**	**EC**	**SC**
FF	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
OP	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)
EC	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.95, 0.05, 0.00)
SC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)
After Investment (Balanced Q matrix)	**FF**	**OP**	**EC**	**SC**
FF	(0.00, 0.00, 0.00)	(0.86, 0.11, 0.02)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
OP	(0.86, 0.11, 0.02)	(0.00, 0.00, 0.00)	(0.84, 0.13, 0.04)	(0.84, 0.13, 0.04)
EC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.95, 0.05, 0.00)
SC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.84, 0.13, 0.04)	(0.00, 0.00, 0.00)

Table 9
The MF-Q values for decision matrix.

Before Investment (initial Q matrix)	FF	OP	EC	SC
STCS	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)
RGD	(0.60, 0.30, 0.10)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)
During Installation (Balanced Q matrix)	**FF**	**OP**	**EC**	**SC**
STCS	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)
RGD	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)
After Investment (Balanced Q matrix)	**FF**	**OP**	**EC**	**SC**
STCS	(0.95, 0.05, 0.00)	(0.86, 0.11, 0.02)	(0.86, 0.11, 0.02)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.86, 0.11, 0.02)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)
RGD	(0.60, 0.30, 0.10)	(0.65, 0.26, 0.09)	(0.91, 0.07, 0.01)	(0.91, 0.07, 0.01)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.91, 0.07, 0.01)

Table 10
The averaged MFN for relation matrix.

	FF	OP	EC	SC
FF	(0.00, 0.00, 0.00)	(0.87, 0.10, 0.02)	(0.85, 0.12, 0.03)	(0.80, 0.15, 0.05)
OP	(0.87, 0.10, 0.02)	(0.00, 0.00, 0.00)	(0.81, 0.14, 0.05)	(0.86, 0.11, 0.03)
EC	(0.67, 0.25, 0.08)	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.95, 0.05, 0.00)
SC	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.81, 0.14, 0.05)	(0.00, 0.00, 0.00)

Table 11
The averaged MFN for decision matrix.

	FF	**OP**	**EC**	**SC**
STCS	(0.90, 0.08, 0.02)	(0.92, 0.07, 0.01)	(0.92, 0.07, 0.01)	(0.80, 0.15, 0.05)
PA	(0.80, 0.15, 0.05)	(0.67, 0.25, 0.08)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)
BES	(0.87, 0.10, 0.02)	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.90, 0.08, 0.02)
RGD	(0.67, 0.25, 0.08)	(0.62, 0.29, 0.10)	(0.94, 0.06, 0.00)	(0.94, 0.06, 0.00)
SI	(0.80, 0.15, 0.05)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.94, 0.06, 0.00)

Table 12
MF vectors for relation matrix.

	MF Vectors
φ_1	[(0.87, 0.10, 0.02), (0.85, 0.12, 0.03), (0.80, 0.15, 0.05)]
φ_2	[(0.87, 0.10, 0.02), (0.81, 0.14, 0.05), (0.86, 0.11, 0.03)]
φ_3	[(0.67, 0.25, 0.08), (0.80, 0.15, 0.05), (0.95, 0.05, 0.00)]
φ_4	[(0.60, 0.30, 0.10), (0.80, 0.15, 0.05), (0.81, 0.14, 0.05)]

according to linear shape are summarized in Table 13.

4.3. *Weighting the factors by MF-BANEW*

Eqs. (18) and (19) compute the entropy and conditional entropy values of the factors. Finally, Eq. (20) determines the weights of the factors. The entropy values and weights of the factors for LS are presented in Table 14.

Table 15 shows the priority order of the factors.

According to Table 15, the most important factor is SC. The fact that the priority order does not change according to the different learning rate and shape shows the consistency and validity of the analysis.

4.4. *Ranking the alternatives by MF-MOPSO*

After the values in Table 9 are averaged with Equation (14), the values are multiplied by weights. Table 16 contains the weighted decision matrix.

Later, the process in section 4.2 is applied for this matrix. The final decision matrix is obtained in Table 17.

Afterwards, Eqs. (21)-(24) is used and the best positions are determined. The results of five iterations are in Table 18.

Table 13
The normalization of relation matrix for LS.

	FF	OP	EC	SC
FF	0	0.378	0.104	0.100
OP	0.378	0	0.121	0.102
EC	0.104	0.121	0	0.195
SC	0.100	0.102	0.195	0

Table 14
Entropy values and weights of the factors for LS.

	$E(F_i)$	$E(F_i \mid F_j)$	$W(F_i)$
FF	1.386	0.832	0.244
OP		0.856	0.234
EC		0.810	0.255
SC		0.781	0.267

Table 15
Comparison analysis results for factors.

LR:0.1	LS	TPS	TS	TBS	OS
FF	3	3	3	3	3
OP	4	4	4	4	4
EC	2	2	2	2	2
SC	1	1	1	1	1
LR:0.5	**LS**	**TPS**	**TS**	**TBS**	**OS**
FF	3	3	3	3	3
OP	4	4	4	4	4
EC	2	2	2	2	2
SC	1	1	1	1	1
LR:1	**LS**	**TPS**	**TS**	**TBS**	**OS**
FF	3	3	3	3	3
OP	4	4	4	4	4
EC	2	2	2	2	2
SC	1	1	1	1	1

Table 16
Weighted decision matrix.

	FF	OP	EC	SC
STCS	(0.22, 0.02, 0.00)	(0.22, 0.02, 0.00)	(0.23, 0.02, 0.00)	(0.21, 0.04, 0.01)
PA	(0.20, 0.04, 0.01)	(0.16, 0.06, 0.02)	(0.24, 0.01, 0.00)	(0.21, 0.04, 0.01)
BES	(0.21, 0.03, 0.01)	(0.19, 0.04, 0.01)	(0.15, 0.08, 0.03)	(0.24, 0.02, 0.00)
RGD	(0.16, 0.06, 0.02)	(0.14, 0.07, 0.02)	(0.24, 0.01, 0.00)	(0.25, 0.02, 0.00)
SI	(0.20, 0.04, 0.01)	(0.14, 0.07, 0.02)	(0.20, 0.04, 0.01)	(0.25, 0.02, 0.00)

Table 17
Final decision matrix for LS.

	STCS	PA	BES	RGD	SI
STCS		0.119	0.083	0.075	0.081
PA	0.119		0.070	0.139	0.127
BES	0.083	0.070		0.064	0.095
RGD	0.075	0.139	0.064		0.147
SI	0.081	0.127	0.095	0.147	

The H values are computed as 0.1002, 0.0999, 0.1020, 0.0982, and 0.0988 respectively. Molecular geometry shapes and learning rates are used to compare the results. The comparison results are given in Table 19.

The results presented in Table 19 demonstrate that the ranking outcomes remain consistent across different molecular geometry shapes and learning rate parameters. This consistency indicates that the proposed model provides stable and reliable evaluation results. To further verify the superiority of the proposed approach, additional statistical comparison analyses are conducted. The Friedman test results indicate that the proposed molecular fuzzy reinforcement learning framework achieves the highest average ranking among the compared methods. Furthermore, the Wilcoxon signed rank test confirms that the performance differences between the proposed model and alternative approaches are statistically significant. These findings provide strong empirical evidence that the proposed framework offers more reliable

Table 18
Iteration results for LS.

	STCS $((V_1)(1))$	PA $((V_2)(1))$	BES $((V_3)(1))$	RGD $((V_4)(1))$	SI $((V_5)(1))$	STCS $((P_1)(1))$	PA $((P_2)(1))$	BES $((P_3)(1))$	RGD $((P_4)(1))$	SI $((P_5)(1))$	$((P_{gb})(1))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
STCS		0.00	0.00	0.00	−0.01	0.00	0.12	0.08	0.08	0.08	0.12	–
PA	−0.01		0.01	−0.01	0.01	0.12	0.00	0.07	0.14	0.13	0.14	–
BES	−0.01	0.00		−0.01	−0.01	0.08	0.07	0.00	0.06	0.10	0.10	–
RGD	−0.01	0.00	0.00		−0.01	0.08	0.14	0.06	0.00	0.15	0.15	–
SI	0.01	−0.01	0.01	0.00		0.08	0.13	0.10	0.15	0.00	0.15	–
	STCS $((\boldsymbol{V}_1)(2))$	**PA** $((\boldsymbol{V}_2)(2))$	**BES** $((\boldsymbol{V}_3)(2))$	**RGD** $((\boldsymbol{V}_4)(2))$	**SI** $((\boldsymbol{V}_5)(2))$	**STCS** $((\boldsymbol{P}_1)(2))$	**PA** $((\boldsymbol{P}_2)(2))$	**BES** $((\boldsymbol{P}_3)(2))$	**RGD** $((\boldsymbol{P}_4)(2))$	**SI** $((\boldsymbol{P}_5)(2))$	$((\boldsymbol{P}_{gb})(2))$	$((\boldsymbol{P}_{gb})(\boldsymbol{t})) - ((\boldsymbol{P}_{gb})(\boldsymbol{t}-1))$
STCS		0.00	0.00	0.01	0.01	0.00	0.12	0.11	0.11	0.11	0.12	0.00
PA	0.01		0.01	−0.01	0.01	0.14	0.00	0.13	0.14	0.14	0.14	0.01
BES	0.00	0.00		0.01	0.00	0.09	0.09	0.00	0.09	0.10	0.10	0.00
RGD	0.02	0.01	0.03		0.00	0.13	0.15	0.13	0.00	0.15	0.15	0.00
SI	0.01	0.01	0.01	0.00		0.13	0.14	0.13	0.15	0.00	0.15	0.00
	STCS $((\boldsymbol{V}_1)(3))$	**PA** $((\boldsymbol{V}_2)(3))$	**BES** $((\boldsymbol{V}_3)(3))$	**RGD** $((\boldsymbol{V}_4)(3))$	**SI** $((\boldsymbol{V}_5)(3))$	**STCS** $((\boldsymbol{P}_1)(3))$	**PA** $((\boldsymbol{P}_2)(3))$	**BES** $((\boldsymbol{P}_3)(3))$	**RGD** $((\boldsymbol{P}_4)(3))$	**SI** $((\boldsymbol{P}_5)(3))$	$((\boldsymbol{P}_{gb})(3))$	$((\boldsymbol{P}_{gb})(\boldsymbol{t})) - ((\boldsymbol{P}_{gb})(\boldsymbol{t}-1))$
STCS		0.00	−0.02	−0.01	0.00	0.00	0.12	0.11	0.11	0.11	0.12	0.00
PA	0.00		−0.02	−0.01	0.00	0.14	0.00	0.13	0.14	0.14	0.14	0.00
BES	−0.01	−0.01		−0.01	0.00	0.09	0.09	0.00	0.09	0.10	0.10	0.00
RGD	−0.02	0.00	−0.02		0.00	0.13	0.15	0.13	0.00	0.15	0.15	0.00
SI	−0.02	0.00	−0.01	0.00		0.13	0.14	0.13	0.15	0.00	0.15	0.00

Table 19
Comparison analysis results for alternatives.

LR: 0.1	**LS**	**TPS**	**TS**	**TBS**	**OS**
STCS	2	2	2	2	2
PA	3	3	3	3	3
BES	1	1	1	1	1
RGD	5	5	5	5	5
SI	4	4	4	4	4
LR: 0.5	**LS**	**TPS**	**TS**	**TBS**	**OS**
STCS	2	2	2	2	2
PA	3	3	3	3	3
BES	1	1	1	1	1
RGD	5	5	5	5	5
SI	4	4	4	4	4
LR: 1	**LS**	**TPS**	**TS**	**TBS**	**OS**
STCS	2	2	2	2	2
PA	3	3	3	3	3
BES	1	1	1	1	1
RGD	5	5	5	5	5
SI	4	4	4	4	4

and robust decision support for evaluating green wind energy park investments.

4.5. Robustness, statistical superiority and sensitivity analysis

Fig. 3 and Table 20 report the convergence characteristics of the ranking stage. Across 50 repeated runs, the mean best objective value increases from 0.10122 at initialization to 0.10192 at iteration 10, while the improvement after iteration 5 falls below 5 x 10ˆ-6.

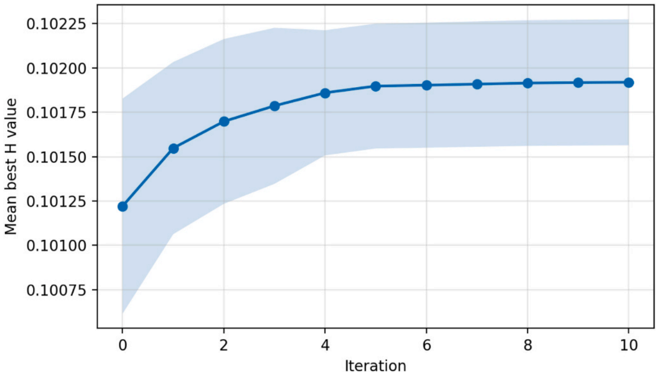


Fig. 3. Convergence behavior of the ranking stage over 50 repeated runs.

Table 20
Convergence statistics of the ranking stage.

Iteration	Mean best H	Std. across runs	Increment vs previous
0	0.10122	0.00061	–
1	0.10155	0.00049	0.000327
2	0.10170	0.00046	0.000150
3	0.10179	0.00044	0.000088
4	0.10186	0.00035	0.000073
5	0.10190	0.00035	0.000038
6	0.10190	0.00035	0.000005
7	0.10191	0.00035	0.000006
8	0.10192	0.00035	0.000006
9	0.10192	0.00035	0.000002
10	0.10192	0.00035	0.000002

In Table 20, the final best H value has a standard deviation of only 0.00035 and a coefficient of variation of 0.35%, and BES is selected as the nearest-best alternative in 96% of the repeated runs. These results indicate both practical convergence and strong run-to-run stability.

To evaluate statistical superiority under uncertainty, 200 perturbation scenarios were generated by varying criteria weights by plus/minus 10% and perturbing expert-derived scores using a local linear sensitivity approximation of the final H layer.

Fig. 4 and Table 21 show that the proposed model achieves the highest mean Spearman rank-stability score (0.856), clearly above TOPSIS (0.461), PROMETHEE II (0.280), and VIKOR (0.149). Wilcoxon

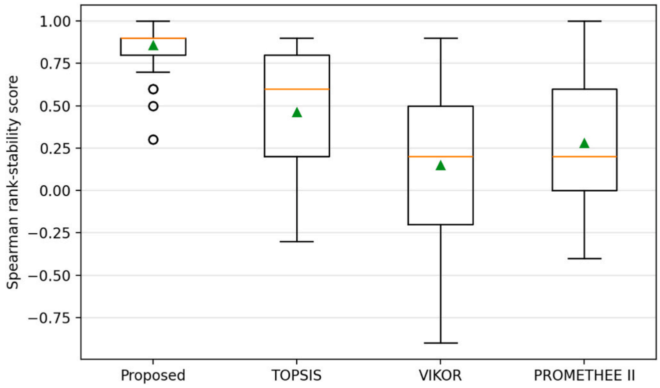


Fig. 4. Distribution of stability scores across 200 perturbation scenarios.

Table 21
Non-parametric statistical comparison against benchmark methods.

Method	Mean stability	Std.	Friedman mean rank	Wilcoxon p vs proposed
Proposed	0.856	0.142	1.03	–
TOPSIS	0.461	0.345	2.28	1.54e-31
VIKOR	0.148	0.397	3.40	3.71e-34
PROMETHEE II	0.280	0.370	3.29	6.08e-34

signed-rank tests against all three baselines are significant at $p < 0.001$, and the Friedman test also indicates a significant overall difference (chi-square = 407.63, $p < 0.001$), with the proposed model ranked first (mean rank = 1.03) Table 22.

The ranking robustness of the proposed model is illustrated in Fig. 5 and Table 24. BES remains rank 1 in 90.0% of perturbation scenarios and rank 2 in the remaining 10.0%. STCS is most frequently ranked second, whereas RGD remains in the last position in 66.5% of the scenarios. In parallel, the weight-stability analysis in Table 25 shows that SC remains the first-ranked criterion in 88.0% of perturbed runs and EC remains second in 69.0% of runs, which supports the stability of the weighting stage despite the single-expert design [63,35] Table 23.

Table 22 reports the eco-environmental indicators. Under the revised assumptions (C = 75 million $, O&M = 1.875 million $/year, r = 8%, n = 20 years, E_t = 153 GWh/year, EF_CO2 = 0.62 kg CO2/kWh, and phi_CO2 = 70 $/ton CO2), the annual avoided carbon-damage benefit is 6.64 million $, the eco-adjusted LCOE becomes 0.0188 $/kWh, and the PBTM is 5.68 years. Hence, including avoided environmental damage considerably strengthens the competitive position of the wind project in the decision space Table 24.

The tornado charts in Figs. 6 and 7 and the numerical values in Table 23 show that capital cost and annual energy output are the most influential parameters. A plus/minus 20% change in capital cost shifts eco-LCOE by up to 0.0100 $/kWh and PBTM by 1.14 years, whereas a plus/minus 20% change in annual energy causes the largest movement in both eco-LCOE (0.0155 $/kWh) and PBTM (0.64 years). The environmental parameters EF_CO2 and phi_CO2 also have material effects because they directly control the avoided carbon-damage benefit [38], Nassar et al. [44].

5. Discussion

One of the renewable energy production methods is green wind energy parks. To increase the effectiveness of green wind energy park projects, it is necessary to select lands with favorable wind potential [15,23]. At the same time, the environmental impacts of these sites should be taken into consideration, and the social cohesion of the facility should be ensured by informing the people in the region where the facility is established about the project [17,62]. Demir et al. [20] stated that wind speed is not the only criterion for determining the location of wind farms. The study also emphasizes the importance of other factors such as bird migration routes, distance to urban areas and land use. Similarly, Salih et al. [55] conducted a multi-criteria analysis using various criteria, especially land cover and infrastructure, to select a suitable location for a wind farm. In the study, it is stated that the improvements made in the wind farm layout increased energy efficiency Table 25.

Table 22
Eco-environmental assumptions and resulting indicators.

Item	Value
Installed capacity	50 MW
Capital cost, C	75.00 million $
Annual O&M cost	1.875 million $/year
Discount rate, r	8%
Project life, n	20 years
Annual energy, E_t	153 GWh/year
Emission factor, EF_CO2	0.62 kg CO2/kWh
Social cost of carbon, phi_CO2	70 $/ton CO2
Avoided carbon-damage cost, C_CO2	6.64 million $/year
Eco-adjusted LCOE	0.0188 $/kWh
PBTM	5.68 years

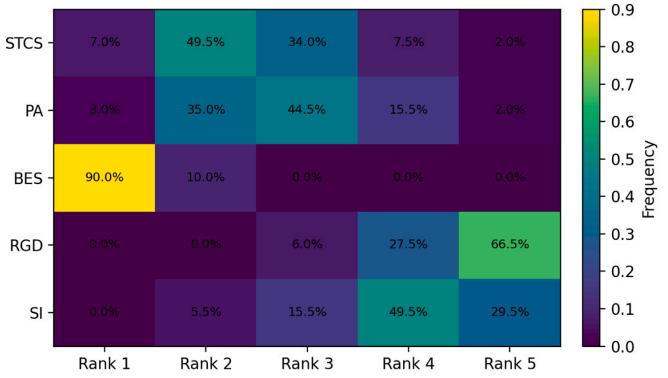


Fig. 5. Rank-frequency heatmap of the proposed model under 200 perturbation scenarios.

Table 23
One-factor sensitivity analysis of the eco-environmental indicators.

Parameter	Low	LCOE low	PBTM low	High	LCOE high	PBTM high
Capital cost, C	−20%	0.0088	4.55	+20%	0.0288	6.82
O&M cost	−20%	0.0163	5.53	+20%	0.0212	5.85
Annual energy, E_t	−20%	0.0343	6.32	+20%	0.0084	5.16
Emission factor, EF_CO2	−20%	0.0275	6.32	+20%	0.0101	5.16
Social cost of carbon, phi_CO2	−20%	0.0275	6.32	+20%	0.0101	5.16

Table 24
Rank-frequency distribution of alternatives under 200 perturbation scenarios.

Alternative	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
STCS	7.0%	49.5%	34.0%	7.5%	2.0%
PA	3.0%	35.0%	44.5%	15.5%	2.0%
BES	90.0%	10.0%	0.0%	0.0%	0.0%
RGD	0.0%	0.0%	6.0%	27.5%	66.5%
SI	0.0%	5.5%	15.5%	49.5%	29.5%

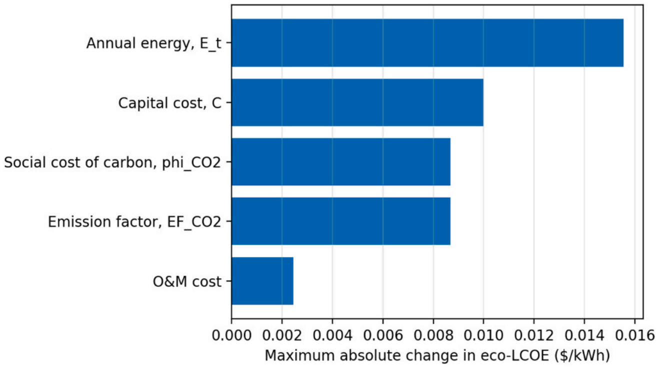


Fig. 6. Tornado sensitivity of eco-adjusted LCOE.

To strengthen the power system perspective of the proposed framework, the implications of the identified strategy alternatives for grid

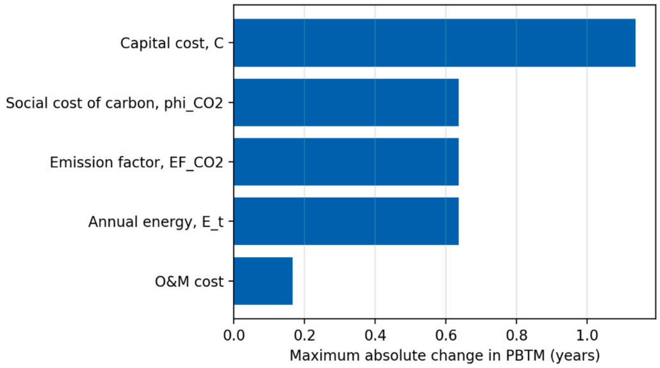


Fig. 7. Tornado sensitivity of payback time money (PBTM).

Table 25
Stability of criterion weights under perturbed relation matrices.

Criterion	Mean weight	Std.	P(rank 1)	P(rank 2)
FF	0.244	0.007	1.5%	16.0%
OP	0.234	0.007	0.0%	3.0%
EC	0.254	0.007	10.5%	69.0%
SC	0.267	0.007	88.0%	12.0%

performance indicators can also be considered. For instance, the integration of balanced energy supply with energy storage integration may significantly reduce wind power curtailment and improve grid flexibility by storing excess electricity during low demand periods and supplying it during peak demand conditions. Similarly, smart turbine control systems can contribute to frequency stability and grid support services by adjusting turbine output according to real time grid conditions [3]. These improvements may lead to higher effective capacity factors, reduced curtailment losses, and improved operational efficiency of the wind energy park. In addition, the integration of storage technologies may reduce reserve requirements and support grid code compliance by providing ancillary services such as frequency regulation and voltage support [27]. Therefore, the strategy rankings obtained in this study are also consistent with key power system performance metrics that are widely considered in electrical power system planning and operation.

The results obtained from the proposed decision-making framework also provide several practical engineering implications for wind energy park operation and planning. The identification of balanced energy supply with energy storage integration as the most appropriate strategy indicates the importance of incorporating storage systems to improve operational flexibility and reduce curtailment losses. For a wind farm with an installed capacity of 50 MW, integrating a battery energy storage system with a capacity in the range of 10–15% of the installed capacity could significantly enhance the ability of the system to manage power fluctuations and support grid stability. Similarly, the high ranking of smart turbine control systems highlights the importance of advanced control strategies such as pitch control optimization, real time power output adjustment, and grid support functionalities. These technologies can improve key operational indicators such as capacity factor, energy yield, and frequency regulation capability. Therefore, the findings of this study suggest that combining energy storage integration with advanced turbine control technologies can substantially improve the overall efficiency and grid compatibility of wind energy park projects.

Ecological compatibility is another significant criterion for maximizing the effectiveness of green wind energy park investments. Strong ecological compatibility means that the planned facility is in harmony with the environment. For example, the wind park planned to be established in the terrestrial area should be structured in a way that does not affect the migration route of birds [12]. Additionally, Şahin et al. [49] emphasized that one of the important criteria in choosing a suitable location for wind farms is land cover and topographic features. However, Morant et al. [39] stated that safe areas that will protect biodiversity should be selected for the establishment of wind energy production facilities. Danovaro et al. [18] defined that the location of the wind farms should be determined in accordance with the Environmental Impact Assessment (EIA) criteria. In the study, it was stated that in the selection of the appropriate location for floating wind farms, the geographical region that will not affect the habitats of marine species should be selected. On the other side, Wang et al. [61] identified that solutions should be developed to reduce the ecological impacts of offshore wind farms on the sea. In addition, the impact of ecological impacts on the food chain was also discussed in the study.

The eco-environmental and robustness layers refine the engineering interpretation of the results. The carbon-damage benefit of 6.64 million $/year materially reduces eco-LCOE, while the sensitivity analysis shows that project bankability is most exposed to capital cost and annual energy uncertainty. This means that BES and STCS are valuable not only because they improve operational flexibility and grid support, but also because they protect the project against yield volatility and therefore stabilize both economic and environmental performance.

6. Conclusion

This study focuses on the performance of green wind energy park investments by integrating dynamic expert evaluation, Q-learning, molecular fuzzy BANEW, and MOPSO. Key findings emphasize the importance of social compliance and ecological compliance as the most critical performance indicators for the evaluation of wind energy projects. Moreover, the study also identified balanced energy supply through energy storage integration and the implementation of smart turbine control systems as the most effective strategies for optimizing project efficiency. The proposed decision-making model offers practical implications for policymakers and investors by prioritizing strategies. Owing to this situation, long-term sustainability and effectiveness can be obtained for these investments. The primary benefits of the suggested model are considering the time-dependent changes of expert opinions and introducing molecular fuzzy sets.

The specialist opinions utilized in the study may be limited to a specific sectoral or geographical framework. This situation emerges as one of the most important limitations of the study. In this context, the participation of experts from different regions and sectors can be increased in future studies. This situation allows the model to have a wider application area. In addition to this condition, the developed decision-making model focuses only on wind energy parks. In subsequent studies, the model can be adapted to other types of energy. For example, it can be adapted and tested for different renewable energy investments such as hydroelectric and solar energy. With the help of this issue, the proposed model can help many more investors. Moreover, in future studies, analyzes can be expanded depending on different scenarios. In this context, a possible global economic crisis, a new epidemic disease or war between countries can be considered as different scenarios. This situation can test the variability of the obtained results according to different conditions.

This study provides an integrated decision-making framework for evaluating wind energy park investment strategies; however, several limitations should be acknowledged. First, the empirical analysis is based on a specific onshore wind energy project with a capacity of 50 MW, which may limit the generalizability of the findings to other wind energy systems with different technical and geographical characteristics. Second, the expert evaluations used in the analysis represent a limited knowledge source and may not fully capture the diversity of opinions that could emerge from a larger expert panel. In addition, the proposed framework focuses primarily on strategic investment evaluation rather than detailed electrical power system operation modeling. Future research may extend the proposed framework by incorporating multiple wind energy projects from different geographical regions, integrating larger expert datasets, and including additional power system performance indicators such as reliability metrics, grid flexibility, and energy storage operation strategies. Furthermore, future studies may explore the integration of alternative optimization techniques and stochastic modeling approaches to further improve the robustness and applicability of renewable energy investment decision models. The proposed framework demonstrates not only deterministic consistency but also statistical robustness: the ranking stage converges rapidly, the weighting stage remains stable under perturbed relation matrices, and the proposed model statistically outperforms the selected baseline MCDM methods under 200 uncertainty scenarios. At the same time, the added limitation text makes clear that perturbation-based robustness is not a substitute for new field evidence; future research should still validate the framework with multiple experts, multiple wind projects, and richer project-specific operational datasets.

CRediT authorship contribution statement

Gang Kou: Methodology. **Serhat Yüksel:** Writing – original draft, Conceptualization. **Hasan Dinçer:** Writing – original draft. **Merve Acar:** Writing – review & editing. **Serkan Eti:** Writing – review & editing, Resources. **Ümit Hacıoğlu:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research is partially supported by the science and technology innovation Program of Hunan Province #2024RC4008.

Appendix

Table A1
Comparison of the proposed study with existing literature on wind energy investment evaluation.

Study	Application Area	Methodology	Dynamic Expert Evaluation	Uncertainty Modeling	Strategy Optimization	Main Contribution
Ahmed et al. [2]	Renewable energy investment analysis	Multi-criteria decision making methods	No	Conventional fuzzy approaches	No	Evaluates renewable energy investment factors
Aqila et al. [8]	Wind energy project assessment	Decision support models	No	Deterministic evaluation	No	Focuses on technical feasibility of wind projects
Aqila et al. (2025b)	Renewable energy project planning	MCDM techniques	No	Limited uncertainty representation	No	Identifies key criteria for renewable investments
Saleem and Abas [50]	Renewable energy planning	Economic and technical analysis	No	Deterministic models	No	Evaluates cost and feasibility aspects
Mósesdóttir [40]	Energy justice and sustainability	Policy and socio-economic analysis	No	Qualitative assessment	No	Examines socio-economic impacts of wind energy
This study	Green wind energy park investments	Q-learning + MF-BANEW + MF-MOPSO	Yes	Molecular fuzzy modeling	Yes	Dynamic expert-based decision framework for identifying optimal investment strategies

Table A2
Linguistic-to-molecular-fuzzy mapping.

Linguistic term	Interpretation	MFN triplet
H	High influence / high suitability	(0.95, 0.05, 0.00)
M	Medium influence / medium suitability	(0.80, 0.15, 0.05)
S	Small influence / low suitability	(0.60, 0.30, 0.10)

Table A3
Finite-MDP specification of the Q-learning temporal balancing stage.

Element	Definition
State, $s_p^{(k)}$	MF relation or decision matrix for period p at iteration k.
Action set, A	{reward-adjust, penalty-adjust, keep} applied entry-wise.
Reward,$r_p^{(k)}$	$-\left\lvert Q_p^{(k+1)} - Q_{(best)} \right\rvert_1$, so smaller discrepancy gives higher reward.
Transition	Deterministic update through the Q-balancing equation and learning rate eta = 0.1.
Terminal rule	Stop when $\max\left\lvert Q^{(k+1)} - Q^{(k)} \right\rvert < \epsilon = 0.02$.

Table A4
Worked entropy example from the normalized relation matrix.

Criterion	Non-zero normalized entries	Conditional entropy, H_i	Divergence, $\ln(4) - H_i$	Weight
FF	0.378, 0.104, 0.100	0.833	0.553	0.244
OP	0.378, 0.121, 0.102	0.856	0.530	0.234
EC	0.104, 0.121, 0.195	0.810	0.577	0.255
SC	0.100, 0.102, 0.195	0.782	0.604	0.267

Table A5
Explicit decision-variable and benchmark design for the ranking stage.

Component	Explicit definition
Particle position	$x = [x_1, x_2, x_3, x_4, x_5]$ over {STCS, PA, BES, RGD, SI}.
Constraint set	$x_i \in [0, 1]$ and $\sum_{i=1}^{5} x_i = 1$.
Objective 1	Maximize the global performance score H of the alternative portfolio.
Objective 2	Minimize imbalance among criterion satisfactions so that overly asymmetric solutions are penalized.
Objective 3	Maximize the pairwise dominance margin among alternatives in the final decision layer.
Benchmark methods	TOPSIS, VIKOR, and PROMETHEE II computed from the same crisp score matrix for non-parametric statistical comparison.

Data availability

No data was used for the research described in the article.

References

[1] Ahmad S, Agrira A, Nassar Y. The impact of loss of power supply probability on design and performance of wind/pumped hydropower energy storage hybrid system. Wadi Alshatti Univ J Pure Appl Sci 2025:52–62.

[2] Ahmed B, Nassar Y, El-Khozondar H, Khaleel M. Optimal design of hybrid renewable energy system (PV/Wind/PHS) under multiple constraints of connection to the electricity grid: a case study. Wadi Alshatti University J Pure Appl Sci 2026: 83–93.

[3] Akbari E, Naghibi AF, Veisi M, Pirouzi S, Safaee S. High voltage direct current system-based generation and transmission expansion planning considering reactive power management of AC and DC stations. Sci Rep 2025;15(1):15537.

[4] Alfathi SA, Miskeen G, Mremi W. Evaluation and prediction performance of solar panel and wind turbine systems using simulation. Wadi Alshatti Univ J Pure Appl Sci 2026:94–104.

[5] Ali S, Khan KA, Gyamfi BA, Ofori EK, Tetteh D, Shamansurova Z. Can clean energy and technology address environmental sustainability in G7 under the pre-set of human development? EnvironSci Pollut Res 2024;31(9):13800–14.

[6] Alshehhi M, Alkhalidi A, Dweiri F. Investigating factors influencing the adoption and sustainable development of wind energy in the UAE. International Journal of Thermofluids 2024;22:100680.

[7] Amhimmid AA, El-Osta WA, Nassar YF, El Khozondar HJ, Salem MA. Financial modeling of social and environmental impacts of wind farm in urban zones: a case study of Zawia-Libya. Int J Energy Environ Eng 2024;15(04).

[8] Aqila A, Nassar Y, El-Khozondar H, Suliman S. Design of hybrid renewable energy system (PV/wind/battery) under real climatic and operational conditions to meet full load of the residential sector: a case study of a house in Samno Village–southern region of Libya. Wadi Alshatti Univ J Pure Appl Sci 2025:168–81.

[9] Ba-abbad MA, Alrougy I, Alalweet F. Techno-economic analysis of implementing pumped hydro energy storage to store solar and wind energy in water-stressed areas. J Storage Mater 2024;98:113024.

[10] Balotari-Chiebáo, F., & Byholm, P. (2024). Quantifying land impacts of wind energy: a regional-scale assessment in Finland. *Environment, Development and Sustainability*, 1-14.

[11] Boadu S, Otoo E. A comprehensive review on wind energy in Africa: challenges, benefits and recommendations. Renew Sustain Energy Rev 2024;191:114035.

[12] Bolonio L, Moreno E, La Calle A, Montelío E, Valera F. Renewable energy acceleration endangers a protected species: better stop to light a torch than run in the dark. Environ Impact Assess Rev 2024;105:107432.

[13] Brink T. Future sensemaking beyond own business self-interests: insights from offshore wind energy innovation ecosystems. Energies 2024;17(18):4649.

[14] Butt MB, Dilshad S, Abas N, Rauf S, Saleem MS. Design of home load management system for load rationing in Pakistan. Eng Rep 2021;3(3):e12312.

[15] Chaibi M, Ben Ghoulam EM, Khallouk N, Tarik L, El Yousfi Y, El Hmaidi A, et al. A novel fuzzy-multi-criteria-GIS-machine learning approach for onshore wind power plant site selection. Euro-Mediterranean J Environ Integr 2024:1–21.

[16] Chen S, Xiao Y, Zhang C, Lu X, He K, Hao J. Cost dynamics of onshore wind energy in the context of China's carbon neutrality target. EnvironSci Ecotechnol 2024;19: 100323.

[17] Çolak Z. A hybrid MCDM method for enhancing site selection for wind power plants in Turkey. Energy Sustain Dev 2024;82:101536.

[18] Danovaro R, Bianchelli S, Brambilla P, Brussa G, Corinaldesi C, Del Borghi A, et al. Making eco-sustainable floating offshore wind farms: Siting, mitigations, and compensations. Renew Sustain Energy Rev 2024;197:114386.

[19] Dao U, Sajid Z, Khan F, Zhang Y. Safety analysis of blended hydrogen pipelines using dynamic object-oriented bayesian network. Int J Hydrogen Energy 2024;52: 841–56.

[20] Demir A, Dinçer AE, Çiftçi C, Gülçimen S, Uzal N, Yılmaz K. Wind farm site selection using GIS-based multicriteria analysis with Life cycle assessment integration. EarthSci Inf 2024;17(2):1591–608.

[21] Dinçer H, Yüksel S, Olaru GO, Eti S. Integrated information system based on Q-learning algorithm and multi-objective particle swarm optimization with molecular fuzzy-based decision-making for corporate environmental investments. Inf Sci 2024;121757.

[22] El-Khozondar HJ, El-Khozondar RJ, Nassar YF, El-Batta F. Technical-economical-environmental assessment of grid-connected hybrid renewable energy power system for Gaza Strip-palestine. Eng Sci Technol, Int J 2025;69:102120.

[23] Elavarasan RM, Nadarajah M, Shafiullah GM. Multi-criteria decision analysis of clean energy technologies for envisioning sustainable development goal 7 in Australia: is solar energy a game-changer? Energ Conver Manage 2024;321: 119007.

[24] Elmabruk A, Salem M, Khaleel M, Mansour A. Prediction of wind energy potential in Tajoura and Mislata cities. Wadi Alshatti Univ J Pure Appl Sci 2025:125–31.

[25] Elnaggar M, El-Khozondar HJ, Salah WA, Nassar YF, Bashir MJ. Assessing the techno-enviro-economic viability of wind farms to address electricity shortages and Foster sustainability in Palestine. Results Eng 2024;24:103111.

[26] Elnaggar M, Salah WA, El-Khozondar HJ, Nassar YF, Bashir MJ. Leveraging wind energy for electricity and hydrogen production: a sustainable solution to power shortages and eco-friendly alternative fuel. Adv Energy Sustainability Res 2026;7 (2):e202500049.

[27] Emdadi K, Pirouzi S. Benders decomposition-based power network expansion planning according to eco-sizing of high-voltage direct-current system, power transmission cables and renewable/non-renewable generation units. IET Renew Power Gener 2025;19(1):e70025.

[28] Eti S, Yüksel S, Dinçer H, Kalkavan H, Hacioglu U, Mikhaylov A, et al. Assessment of technical and financial challenges for renewable energy project alternatives. Cleaner Eng Technol 2024;18:100719.

[29] Fang W, Liao Z, Bai Y. Improved ACO algorithm fused with improved Q-Learning algorithm for Bessel curve global path planning of search and rescue robots. Rob Auton Syst 2024;182:104822.

[30] Fredershausen S, Meyer-Larsen N, Klumpp M. In: February). Comprehensive Sustainability Evaluation Concept for Offshore Green Hydrogen from Wind Farms. Cham: Springer Nature Switzerland; 2024. p. 309–21.

[31] Gentili PL. The conformational contribution to molecular complexity and its implications for information processing in living beings and chemical artificial intelligence. Biomimetics 2024;9(2):121.

[32] Hasheminezhad A, Nazari Z, Yang B, Ceylan H, Kim S. A comprehensive review of sustainable solutions for reusing wind turbine blade waste materials. J Environ Manage 2024;366:121735.

[33] Jayabal R. Towards a carbon-free society: Innovations in green energy for a sustainable future. Results Eng 2024;103121.

[34] Jung C, Sander L, Schindler D. Future global offshore wind energy under climate change and advanced wind turbine technology. Energ Conver Manage 2024;321: 119075.

[35] Li M-W, Xu R-Z, Geng J, Hong W-C, Li H. A ship motion forecasting approach based on Fourier transform, regularized Bi-LSTM and chaotic quantum adaptive WOA. Ocean Eng 2024;313:119560.

[36] Magsar A, Sumiya E, Dorligjav S, Nyam-Osor N, Ramadan BS, Matsumoto T. In: The role of wind energy to the decarbonization in some Asian countries. Elsevier; 2024. p. 45–64.

[37] Maimó-Far A, Homar V, Tantet A, Drobinski P. The trade-off between socio-environmental awareness and renewable penetration targets in energy transition roadmaps. Appl Energy 2024;355:122397.

[38] Mohammed SM, Nassar Y, El-Osta W, El-Khozondar HJ, Miskeen A, Basha A. Carbon and energy life cycle analysis of wind energy industry in Libya. Solar Energy Sustain Develop J 2023;12(1):50–69.

[39] Morant J, Arrondo E, Sánchez-Zapata JA, Donázar JA, Margalida A, Carrete M, et al. Fine-scale collision risk mapping and validation with long-term mortality data reveal current and future wind energy development impact on sensitive species. Environ Impact Assess Rev 2024;104:107339.

[40] Mósesdóttir L. Energy (in) justice in the green energy transition. the case of Fosen wind farms in Norway. Technol Soc 2024;77:102563.

[41] Nassar YF, El-Khozondar HJ, El-Osta W, Mohammed S, Elnaggar M, Khaleel M, et al. Carbon footprint and energy life cycle assessment of wind energy industry in Libya. Energ Conver Manage 2024;300:117846.

[42] Nassar YF, El-Khozondar HJ, Elnaggar M, El-batta FF, El-Khozondar RJ, Alsadi SY. Renewable energy potential in the State of Palestine: proposals for sustainability. Renewable Energy Focus 2024;49:100576.

[43] Nassar, Y. F., El-Khozondar, H. J., Salem, M. A., Alatrash, A., Salah, W. A., Bashir, M. J., & Elnaggar, M. H. (2025). Technical and environmental cost-benefit analysis of strategies towards a green economy in the electricity sector in Libya. *Economics and Policy of Energy and the Environment*, (2025/2).

[44] Nassar YF, El-Khozondar HJ, Salem MA, Alatrash AA, Elnaggar M, Salah WA, et al. Estimation of CO_2 emission within Libya's electricity generation sector. Next Research 2025;2(3):100567.

[45] Ouerghi FH, Omri M, Menaem AA, Taloba AI, Abd El-Aziz RM. Feasibility evaluation of wind energy as a sustainable energy resource. Alex Eng J 2024;106:227–39.

[46] Prieto-Herráez D, Martínez-Lastras S, Frías-Paredes L, Asensio MI, González-Aguilera D. EOLO, a wind energy forecaster based on public information and automatic learning for the Spanish Electricity Markets. Measurement 2024;231:114557.

[47] Qadir, S. A., Ahmad, F., Al-Motairi, H., bin Saleh Al-Sada, M., & Al-Fagih, L. (2024). Renewable energy incentives for project owners representing communities with heavily subsidised fossil fuel-based electricity. *Sustainable Cities and Society*, *101*, 105152.

[48] Ramalho E, Lima F, López-Maciel M, Madaleno M, Villar J, Dias MF, et al. Understanding wind energy economic externalities impacts: a systematic literature review. Renew Sustain Energy Rev 2025;209:115120.

[49] Şahin G, Koç A, Doğan SŞ, van Sark W. Assessment of wind energy potential and optimal site selection for wind energy plant installations in Igdir/Turkey. Sustainability 2024;16(20):8775.

[50] Saleem MS, Abas N. A solar assisted grid-tied polygeneration system for hydrogen and electricity production: future of energy transition from electrons to molecules. Int J Hydrogen Energy 2024;69:559–69.

[51] Saleem MS, Abas N. Optimal design of renewable driven polygeneration system: a novel approach integrating TRNSYS-GenOpt linkage. Cleaner Eng Technol 2025;24:100856.

[52] Saleem MS, Abas N. Optimization and loss estimation in energy-deficient polygeneration systems: a case study of Pakistan's utilities with integrated renewable energy. Results Eng 2025;25:104001.

[53] Saleem MS, Abas N, Kalair AR, Rauf S, Haider A, Tahir MS, et al. Design and optimization of hybrid solar-hydrogen generation system using TRNSYS. Int J Hydrogen Energy 2020;45(32):15814–30.

[54] Salem M, Elmabruk A, Irhouma M, Mangir I. Assessment of wind energy potential in Western Mountain: Nalut and Yefren as case study. Wadi Alshatti University J Pure Appl Sci 2025:35–42.

[55] Salih A, Hassaballa AA, Eltawil MA. Integrating spatial data and multi-criteria analysis for wind farm suitability mapping in eastern Saudi Arabia. Energy 2024;301:131623.

[56] Santos M, González M. Factors that influence the performance of wind farms. Renew Energy 2019;135:643–51.

[57] Teixeira-Duarte F, Ramos V, Rosa-Santos P, Taveira-Pinto F. Multi-objective decision tool for the assessment of co-located wave-wind offshore floating energy parks. Ocean Eng 2024;292:116449.

[58] Töller AE, Garske B, Rasch D, Weigel A, Hahn H. Failing successfully? local referendums and ENGOs’ lawsuits as challenges to wind energy expansion in Germany. Zeitschrift für Vergleichende Politikwissenschaft 2024:1–29.

[59] Ullah A, Nobanee H, Ullah S, Iftikhar H. Renewable energy transition and regional integration: Energizing the pathway to sustainable development. Energy Policy 2024;193:114270.

[60] Wang L, Wang B, Cen W, Xu R, Huang Y, Zhang X, et al. Ecological impacts of the expansion of offshore wind farms on trophic level species of marine food chain. J Environ Sci 2024;139:226–44.

[61] Wang M, Zhong D, Ali S, Meo MS. The windfall of green finance: advancing environmental sustainability through wind energy. Renew Energy 2024;227:120583.

[62] Yanez-Rosales P, Del Río-Gamero B, Schallenberg-Rodríguez J. Rationale for selecting the most suitable areas for offshore wind energy farms in isolated island systems. Case study: Canary Islands Energy 2024;307:132589.

[63] Yang Z-Y, Cao X, Xu R-Z, Hong W-C, Sun S-L. Applications of chaotic quantum adaptive satin bower bird optimizer algorithm in berth-tugboat-quay crane allocation optimization. Expert Syst Appl 2024;237:121471.