Next Materials 8 (2025) 100747

Contents lists available at ScienceDirect

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Research article

Mass expert group decision-making based on q-learning and molecular fuzzy logic for floating renewable energy materials investments

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A R T I C L E I N F O

Keywords:
Floating renewable energy system
Clean energy
Energy independence
Energy investments

A B S T R A C T

Floating renewable energy systems refer to energy projects deployed on water surfaces, playing a vital role in future energy strategies by promoting the use of sustainable resources. These systems reduce dependency on fossil fuels, meet growing energy demands, and ensure energy security by enabling countries to produce their own energy. The performance of these investments is influenced by technical and environmental factors. Despite their importance, there is a lack of comprehensive studies identifying the most critical factors affecting performance, creating a gap in the literature. This study addresses this gap by developing an innovative decision-making model using information gain, Q-learning, molecular fuzzy cognitive maps, and molecular ranking techniques. Hence, the main purpose is to identify the most critical determinants and optimal strategies for floating renewable energy investments, providing valuable guidance for decision-makers and investors. The study contributes to the literature by providing a structured criterion set for decision-makers. The findings obtained from the study highlight the optimization of areas with multiple uses. According to this criterion, it is possible to use other energy systems in an area other than floating systems. This situation also brings a cost advantage. It also supports purposes such as environmental protection and preventing water waste. Another important criterion, environmental integration, is to create an energy production system that is compatible with the living creatures living here by protecting the natural ecosystem on the water surface where the floating systems will be installed. Furthermore, it introduces novel methodologies that are rarely used in existing studies, such as calculating expert importance weights and modelling complex factor interactions. By addressing these gaps, the study offers both theoretical and practical advancements, ensuring more efficient and sustainable investment strategies in floating renewable energy systems. It is concluded that space optimization with multi-use potential and environmental integration with ecosystem protection are found as the most critical determinants. Tidal energy systems and wave energy converters are the most effective investment alternatives.

1. Introduction

Floating renewable energy systems generally refer to projects placed on the surface of the water. These investments have an important place in the energy strategies of the future. Floating systems increase the use of sustainable resources in energy production. Owing to this situation, countries' dependence on fossil fuels in energy production is decreasing. These projects are also very necessary to meet the increasing energy demand. The increase in the world population and industrialization are constantly increasing the energy demand. Floating systems offer a strong option to meet this need [31]. Furthermore, floating renewable energy systems also play a very key role in ensuring energy security. The dependence of these countries on energy imports is decreasing. In addition to them, these systems are also very necessary in terms of

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https://doi.org/10.1016/j.nxmate.2025.100747
Received 6 March 2025; Received in revised form 11 May 2025; Accepted 20 May 2025
Available online 24 May 2025

saving space. Unlike land-based energy plants, floating projects do not occupy arable land. Energy resources are generally more concentrated in the seas and on water surfaces [17]. This situation allows for the production of higher amounts of energy. Floating renewable energy systems are important for ensuring energy security and meeting energy demand. For example, one of the steps to meet the energy demand and reduce carbon emissions in China is to increase the number of floating systems [29]. In another study, floating solar energy systems in China will contribute to renewable energy production in addition to hydroelectric systems. Solar systems installed in this way will save more land compared to solar panels on land [5].

The performance of floating renewable energy system investments is affected by both technical and environmental factors. The potential of wind and solar resources is one of the environmental factors that are important in this process. For example, performance increases in regions where wind speed and continuity are high. High waves are other environmental factors that can affect the stability of floating platforms. Excessive wave heights can damage energy production equipment [26]. Climate and weather conditions also play a very important role in this process. Extreme temperature changes can negatively affect the efficiency of projects. The use of durable materials can reduce the possibility of system failures. Owing to this situation, maintenance and repair costs of projects can be significantly reduced [2]. On the other hand, improvements in financial factors are also very necessary in this process. Conducting research studies for more efficient technologies can contribute to reducing costs in the long term.

It is necessary to determine the most important factors affecting the performance of floating renewable energy system investments. Budget, time and human resources are limited in energy projects. These resources can be used efficiently by focusing on the most critical factors. On the other hand, identifying and solving the risks that directly affect the success of the project at an early stage prevents future losses. The fact that there are few studies in the literature on the most important factors in a developing field such as floating renewable energy system is a significant deficiency. Although existing studies [20,42,50] emphasize the importance of the factors, studies analyzing the most important ones are limited. In studies where priority analysis is performed, the motivation is to provide the right investment suggestion to businesses with limited budgets. For this reason, a comprehensive priority analysis should be conducted to determine the most important factor. Thus, businesses will be able to make the right investment decision by using their resources efficiently. This inadequacy in the literature means the lack of data needed for investors. This study aims to find the critical indicators for floating renewable energy system investments by a new model. Information gain methodology and q-learning algorithm are considered to select the most appropriate experts. Moreover, molecular fuzzy-based cognitive maps and molecular ranking techniques are used to develop effective investment strategies for these projects. Thus, following research question can be created. (1) Which determinants of floating renewable energy system investments have the highest significance? (2) Which investment alternatives should be priorly considered?

There are limited studies in the literature on determining the most critical factors related to floating renewable energy system investments. This deficiency means that the necessary information cannot be provided for investors and decision makers. This issue can be stated as the most important motivation for conducting the priority analysis in this study. Budget, time and human resources are generally limited in energy projects. Therefore, determining the most important factors ensures the effective use of these resources. However, there is no clear consensus on which are the most important criteria. Determining the most critical factors in this study can also address this gap in the literature. Determining the factors and risks that directly affect the success of projects at an early stage helps prevent possible losses in the future. The study aims to help investors make the right decisions by determining the most important determinants and priority investment alternatives in floating renewable energy system investments.

The most important contributions of this study to the literature are related to the innovative approaches and information provided at both theoretical and applied levels. The deficiencies in the literature regarding the determination of the most important factors related to floating renewable energy system investments are addressed. The study aims to eliminate this uncertainty and provides a set of criteria that serve as a guide for decision makers. The novelties of the decision-making model created by using innovative methods are also stated below. (1) The study optimizes expert selection and determination of the most important factors by using innovative approaches such as information gain method and q-learning algorithm. These methods provide an original methodological framework that is not common in the literature. In the vast majority of decision-making models in the literature, the importance weights of experts are not calculated. (2) The molecular fuzzy cognitive maps approach helps to understand complex relationships by modelling the interactions and dependencies between factors. Owing to this condition, it can analyze the effects of factors and changes in their relationships over time. The greatest advantage of this application is that it can analyze the dependencies between factors that are ignored in traditional decision-making models. (3) The use of molecular ranking technique also provides some advantages to the model. In this process, a molecular geometry-based ranking is performed. In this framework, a comprehensive analysis can be performed with different shapes in the molecular geometry approach. With the help of this issue, investment alternatives can be ranked in the most appropriate way and the most efficient investment strategies can be selected. The biggest advantage of this situation is that it provides more sensitive and consistent results than traditional ranking methods.

Section 2 (Literature Review) presents an in-depth analysis of existing studies related to floating renewable energy systems. The research gap is highlighted and the need for a new model to determine critical factors is explained. Section 3 (Methodology) outlines the innovative techniques employed in this study. Section 4 (Analysis Results) provides a detailed examination of the findings derived from the proposed model, emphasizing the most significant factors and investment alternatives. Section 5 (Discussion) interprets these results in the context of the broader energy sector, addressing implications for practice and policy. Section 6 (Conclusion) summarizes the key contributions of the study, underlining its importance for both academic research and practical applications in renewable energy investments.

2. Literature review

Floating renewable energy generation systems are important for green energy production [19]. The structural durability can increase the effectiveness of floating renewable energy investments. This feature is important for the design, reliability and economic life of floating renewable energy generation facilities [43]. Indeed, Djalab et al. [18] found that increasing the structural resilience capability of the system in floating power generation systems will reduce production costs. The study also emphasized that structural resilience increases efficiency and reliability. However, Ramanan et al. [41] highlighted that new technologies should be developed to increase durability in floating power generation systems. It is stated that these technologies to be developed in the study should focus on floating structure designs, robust instrumentation, wireless monitoring and sensing capabilities. Finally, O'Neill and Mehmanparast [39] focused on the need to develop technology to increase the durability of mechanical structures in floating energy structures. They also stated that Additive Manufacturing (AM) technology would be more efficient to extend the lifetime of offshore renewable energy structures.

Environmental integration can improve the effectiveness of investments in floating energy systems. Environmental compatibility means that offshore energy systems operate in an integrated manner with natural systems by minimizing their environmental impacts. This concept enables floating renewable energy systems to be developed in line with sustainability goals without harming the environment [47]. Firstly, Ali et al. [1] in his study included the issues to be considered for site selection in floating renewable energy systems. He stated that environmental protection laws and legal restrictions are one of the important factors affecting site feasibility. In addition; Benjamins et al. [3,4] emphasized that floating photovoltaic systems have environmental impacts. However, it is noted that the environmental compliance of these systems should be increased with appropriate monitoring methods and scaling. It is also underlined that floating solar energy systems have an important role in global decarbonization. Nagababu et al. [37] proposed a floating solar panel system to meet the energy demand arising with the rapid increase in population. This system is expressed as an innovative and environmentally friendly production system against terrestrial energy production systems.

Space optimization with multi-use potential is among the criteria required to increase the effectiveness of floating renewable energy systems investments. In addition to the most efficient use of available space, floating energy systems are designed to perform different functions together, which increases the space optimization and multi-use potential of these systems [9]. Indeed, Nguyen et al. [38] stated that floating energy systems can be useful to meet the energy needs in shrimp farming. In the study, it was emphasized that most of the electricity from the national electricity grid comes from fossil fuels and contributes to environmental pollution. Similarly, Danovaro et al. [10] highlighted that floating energy systems should be designed in accordance with the ecosystem for the sustainable use of marine areas. Zhao et al. [52] stated that floating energy systems in the open seas will meet the need for freshwater production as well as energy needs on offshore islands. Guşatu et al. [23] underlined that offshore energy systems can be integrated into maritime activities. Thus, the energy need in these areas will also be met.

Distribution efficiency with grid infrastructure is an important factor in increasing investments in floating renewable energy systems. Appropriate grid infrastructure leads to increased efficiency in renewable energy generation. Therefore, technological innovations and infrastructure planning should be prioritized to strengthen the grid infrastructure [25]. Indeed, Shao et al. [44] emphasized the importance of early-stage warning systems and classification tools in offshore wind energy system. The development of these systems is important for both environmental sustainability and cost efficiency. Similarly, [27] found that wake-up effects cause energy losses in offshore wind farms. The study proposes a new system to improve the grid infrastructure to prevent energy losses. Martinez-Puente et al. [36] calculate the fatigue life of floating renewable energy generation plants under various scenarios. With the findings obtained, suggestions to increase the efficiency of the system are presented.

Decision-making models are frequently used in floating renewable energy materials investments [34]. The main reason for this is that these techniques are very successful in priority analysis. With these models, the most critical indicators that affect the performance of investments can be identified [48]. For this reason; Deveci et al. [11] stated in their study that decision-making models are suitable for planning offshore wind farm locations. Similarly, in another study, Gökmener et al. [22] used sine trigonometric decision-making models to determine the most appropriate criteria for site selection in floating photovoltaic energy systems. In another study, [13] utilized decision-making models to select the optimal port for offshore wind energy generation and storage systems. Finally, Díaz and Soares [12] performed a priority analysis using decision-making models to determine the optimal location for the installation of floating wind farms. In the study, it was stated that Portugal is the most suitable country for floating wind farms.

The literature is reviewed, and some findings can be reached. Floating energy systems provide clean and easy access to energy for regions where terrestrial energy production is insufficient and there are difficulties in accessing energy. In this respect, it has an important place among energy production methods. However, these projects have various challenges as they require technological infrastructure and environmental adaptation. Therefore, to develop effective investment strategies, it is necessary to prioritize among many factors. Moreover, the number of these studies is limited in the literature. Therefore, to fill this gap, a priority analysis should be conducted by considering the factor pool.

3. Methodology

Mass expert group decision making based on Q learning and MF logic are used to rank investment alternatives for floating renewable energy systems. This decision-making model includes appropriate decision maker (Dec. Mkr.) selection, creating of balanced evaluation matrices and MF-based MCDM technique. In this context, in the first step, the information gain-based mass dec. mkr. selection model is applied. Thus, the most suitable Dec. Mkr.s within the Dec. Mkr. group are determined. In the next step, the evaluation matrices obtained with the Dec. Mkr. evaluations are made more balanced according to the most successful Dec. Mkr. with Q-learning. In the last step, both the criteria are weighted and the investment alternatives for floating renewable energy systems are ranked with cognitive maps based MOPSO. In this process, uncertainty is minimized by integrating fuzzy logic. For this purpose, Molecular Fuzzy Number (MFN) is used. Fig. 1 reflects the flow of the process.

3.1. Information gain-based mass Dec. Mkr. selection

Working with a mass group of Dec. Mkr.s not only complicates the analysis, but also identifying appropriate Dec. Mkr.s is one of the main problems of decision-making models. To overcome such problems, a model based on information acquisition is proposed. While the information of Dec. Mkr.s is used as the input of this model, the primary ratings of Dec. Mkr.s about the criteria are used as the output of the model. Thus, the model measures the impact of each Dec. Mkr. information on the criteria by calculating the information gain. Thus, the aim of the model is to identify the most relevant Dec. Mkr.s from large member of Dec. Mkr. group. The stepwise calculation of the model is shown below [45].

Between input and output values, Eq. (1) analyzes the entropy of each output.

$$\mathcal{E}(C) = -\sum_{i=1}^{n} p_i \log_2(p_i) \tag{1}$$

Where C refers to the criterion in the output. p_i equals to probability of each rating and n means the level of the unique ratings. In the other step, Eq. (2) is about computing information gain values for each input.

$$\mathbb{I}(A, C) = \mathcal{E}(C) - \sum_{v \in A} \frac{|C_v|}{|C|} \mathcal{E}(C_v) \tag{2}$$

Where $|C_v|$ is the size of subset of C for v-input. Similarly, $|C|$ is the size of ratings. Next, the weighted entropy for each output is obtained. In this manner, the overall entropies mean the information gain value for the input on the selected output. After that, this calculation is repeated for all of pairings. Finally, the appropriate Dec. Mkr. inputs with the highest value of the information gain are determined for each output. So, it is possible to construct the rules that define the most influential Dec. Mkr. information.

3.2. Q-Learning

The experience of Dec. Mkr.s is effective in the formation of the elements of the evaluation matrices. The algorithm of this model, which accepts the evaluation matrix of the most experienced Dec. Mkr. as the initial matrix and balances the matrix of other Dec. Mkr.s, performs

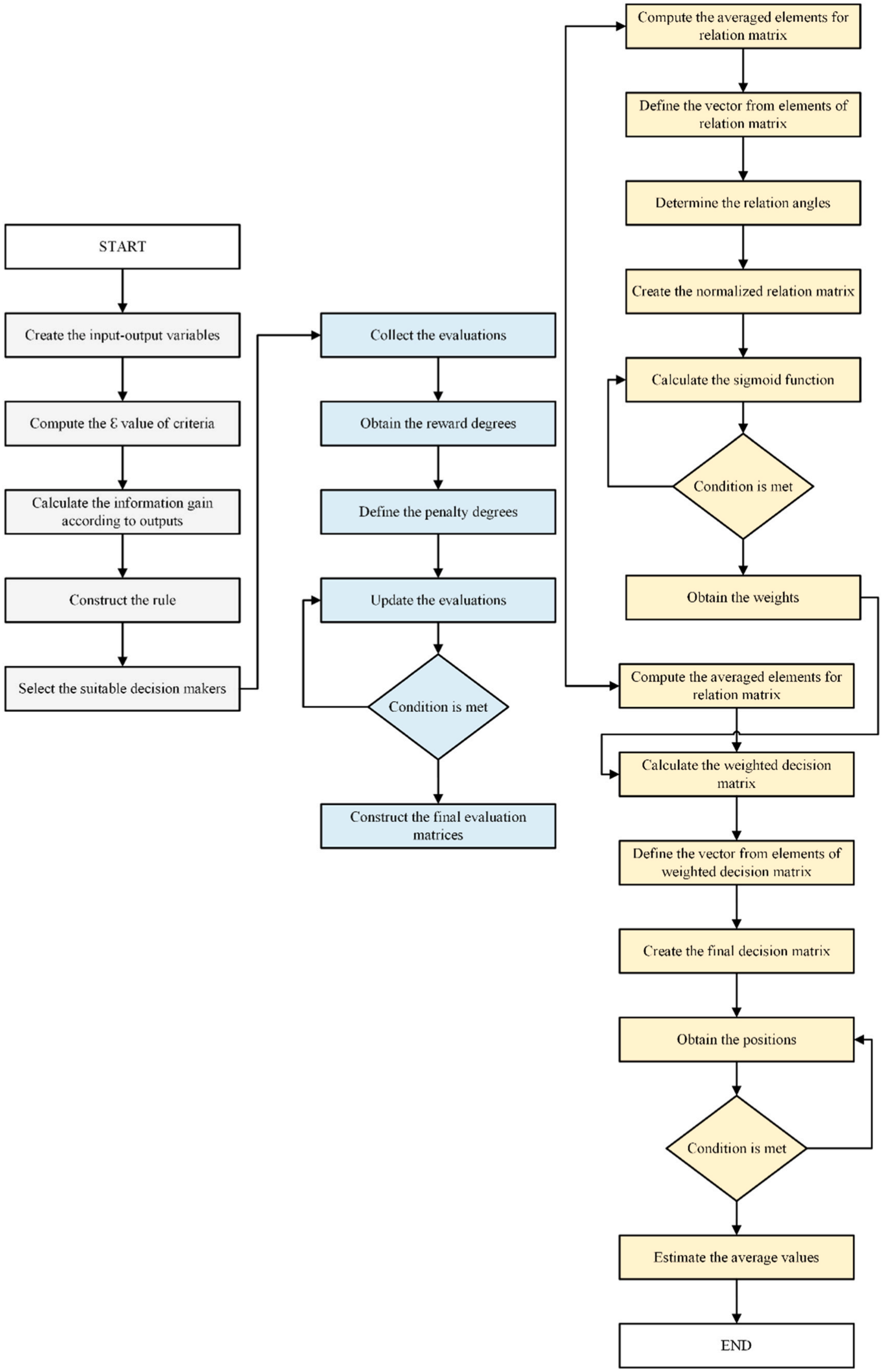

Fig. 1. The flow of the process.

iterations with the help of reward, penalty and learning rate parameters. The stepwise calculation of the model is detailed below [15,14].

Firstly, the evaluations are collected using linguistic scales. Later, the evaluations are transformed to MFN. Eq. (3) creates the reward degrees among the most experienced and others Dec. Mkr.s.

$$\mathscr{R}_{s,a} = r \cdot \left(Q_{s,a\quad(initial)} - Q_{s,a\quad(other)}\right) \tag{3}$$

Where r is factor of reward and equals to weight of less experienced Dec. Mkr. Similarly, Eq. (4) constructs the penalty degrees among the most experienced and others Dec. Mkr.s.

$$\mathscr{P}_{s,a} = p \cdot \left(Q_{s,a\quad(other)} - Q_{s,a\quad(initial)}\right) \tag{4}$$

Where p is factor of penalty and equals to weight of the most experienced Dec. Mkr. Afterwards, Eq. (5) is about updating the elements of evaluation matrix according to learning rate (α).

$$Q_{s,a}^{updated} = Q_{s,a\quad(initial)} + \alpha \cdot \left(\mathscr{R}_{s,a} - \mathscr{P}_{s,a}\right) \tag{5}$$

The small value of α indicates that learning process is updated slowly with few stabilities. The big value of α could lead to rapid and more responsive results with the risk of overshooting. To obtain the final evaluation matrices, the maximum value of the absolute difference between the initial and updated elements must remain smaller than the threshold value. The iteration continues until this convergence check is met, when this convergence check is met, the final evaluation matrix is obtained.

3.3. Cognitive maps-based MOPSO with MFS

The MCDM technique is used to obtain the optimal solution in the decision-making problem. There are two models at the core of this technique. The first model is the cognitive map and is preferred to calculate the criteria weights by evaluating the degrees of dependency between the criteria. Then the second model comes into technique and is used to rank the alternatives evaluated according to the criteria [45]. This technique, which is created by the integration of these two models, is based on the evaluations of the Dec. Mkr.s. For this reason, the technique uses MFNs to analyze linguistic uncertainty. The stepwise calculation of the technique is introduced below.

Firstly, the relation matrix is constructed by averaging the balanced MF Dec. Mkr.s' evaluations. Eq. (6) is used for this.

$$\mathscr{r} = \left(\bigcup_{i=1}^{k} \mathscr{r}_i\right) = \left\{\left(u, \frac{1}{k}\sum_{i=1}^{k} \mu_{\mathscr{r}_i}(u), \frac{1}{k}\sum_{i=1}^{k} \nu_{\mathscr{r}_i}(u), \frac{1}{k}\sum_{i=1}^{k} \xi_{\mathscr{r}_i}(u)\right) | u \in U\right\} \tag{6}$$

Where $\mathscr{r}$ is the element of relation matrix and the number of Dec. Mkr.s is k. In addition, μ, ν, ξ are the components of the MFNs. These components are named membership, non-membership and hesitant degrees. In addition, the sum of these components equals to 1 for u to U. Eq. (7) defines the vectors.

$$u_i = \left[(\mu_{i1}, \nu_{i1}, \xi_{i1}), (\mu_{i2}, \nu_{i2}, \xi_{i2}), \ldots \left(\mu_{i(n-1)}, \nu_{i(n-1)}, \xi_{i(n-1)}\right)\right] \tag{7}$$

Since each criterion has no dependency on itself, each vector has n-1 elements for n criteria. After the vectors are defined, the cosine of the angle between any two vectors is calculated by vector product and magnitude of the vector as in Eq. (8).

$$\cos(\theta_{u_i,u_j}) = \frac{\sum_{t=1}^{n-1}\left(\mu_{i,t}\cdot\mu_{j,t} + \nu_{i,t}\cdot\nu_{j,t} + \xi_{i,t}\cdot\xi_{j,t}\right)}{\left(\sum_{t=1}^{n-1}\left(\mu_{i,t}^2 + \nu_{i,t}^2 + \xi_{i,t}^2\right)\right)\cdot\left(\sum_{t=1}^{n-1}\left(\mu_{j,t}^2 + \nu_{j,t}^2 + \xi_{j,t}^2\right)\right)} \tag{8}$$

The angle values are normalized, and Eq. (9) defines the piecewise function used to obtain the normalized angles.

$$f(x) = \begin{cases} \dfrac{x}{\theta_{\max}}; general \\ \dfrac{x}{\pi}; linear \\ \dfrac{x}{\frac{2\pi}{3}}; trigonal\ planar \\ \dfrac{x}{\frac{\pi}{2}}; tetrahedral \\ \dfrac{x}{\frac{2\pi}{5}}; trigonal\ bipyramidal \\ \dfrac{x}{\frac{\pi}{3}}; octahedral \end{cases} \tag{9}$$

In the function, the angle values for the first case are divided by the maximum of the angles for normalization. GS1 for linear, GS2 for trigonal planar, GS3 for tetrahedral, GS4 for trigonal bipyramidal, and GS5 for octahedral are identified in the function. In the next step, Eq. (10) is used for the reciprocal value.

$$recip\left(\theta_{u_i,u_j}\right) = \frac{1}{f\left(\theta_{u_i,u_j}\right)} \tag{10}$$

Afterwards, the normalized relation matrix is constructed. Eq. (11) is about calculating the elements of the normalized relation matrix.

$$\mathscr{n}_{ij} = \frac{recip\left(\theta_{u_i,u_j}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} \tag{11}$$

State vectors are determined by Eq. (12).

$$A(t) = [a_1(t), a_2(t), \ldots, a_n(t)] \tag{12}$$

Where A(t) means the activation degrees of the criteria for iterations. After definition of the state vectors, Eq. (13) updates the state vectors.

$$sigmoid(A(t)\cdot NR) = \frac{1}{1 + e^{-A(t)\cdot NR}} \tag{13}$$

Where NR is the normalized relation matrix. This function is calculated repeatedly until two consecutive values are equal. In the iteration where the results are equal, the calculation is stopped and the value sequence from the last iteration is normalized. Eq. (14) presents the finding of the criteria weights.

$$\mathscr{w}_j = \frac{sigmoid_j^{lastiteration}}{\sum_{j=1}^{n} sigmoid_j^{lastiteration}} \tag{14}$$

By determining the weights of the criteria, the first model is completed, and the second model comes into technique. Firstly, the decision matrix is constructed by averaging the balanced MF Dec. Mkr.s' evaluations with the help of Eq. (6). Afterwards, the vectors are created from the elements of weighted decision matrix. Eq. (15) defines the vectors [15,14].

$$y_i = [(\mu_{i1}, \nu_{i1}, \xi_{i1}), (\mu_{i2}, \nu_{i2}, \xi_{i2}), \ldots (\mu_{im}, \nu_{im}, \xi_{im})] \tag{15}$$

After the vectors are defined, the cosine of the angle between any two vectors is calculated by vector product and magnitude of the vector via Eq. (16).

$$\cos(\theta_{y_i y_j}) = \frac{\sum_{t=1}^{m}\left(\mu_{i,t}\cdot\mu_{j,t} + \nu_{i,t}\cdot\nu_{j,t} + \xi_{i,t}\cdot\xi_{j,t}\right)}{\left(\sum_{t=1}^{m}\left(\mu_{i,t}^2 + \nu_{i,t}^2 + \xi_{i,t}^2\right)\right)\cdot\left(\sum_{t=1}^{m}\left(\mu_{j,t}^2 + \nu_{j,t}^2 + \xi_{j,t}^2\right)\right)} \tag{16}$$

The angle values are normalized, and Eq. (9) defines the piecewise function used to obtain the normalized angles. In the next step, Eq. (17) is used for the reciprocal value.

$$recip\left(\theta_{y_i y_j}\right) = \frac{1}{f\left(\theta_{y_i y_j}\right)} \tag{17}$$

Afterwards, the final decision matrix is constructed. Eq. (18) is about computing the elements of the final decision matrix.

$$\mathfrak{f}_{ij} = \frac{recip\left(\theta_{y_i,y_j}\right)}{\sum_{j=1}^{m} recip\left(\theta_{y_i,y_j}\right)} \tag{18}$$

Eq. (19) defines the particle presentation for the potential solutions.

$$X_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\} \tag{19}$$

After that, $V_{ij}(1)$ is the initial velocity, equal to $\partial \times \left(P_{\max_i} - P_{\min_i}\right) \times r$, and the velocity of each particle is determined by Eq. (20).

$$V_{ij}(t+1) = \omega V_{ij}(t) + c_1 r_1 \left(P_{ij}(t) - X_{ij}(t)\right) + c_2 r_2 \left(P_{gb_j}(t) - X_{ij}(t)\right) \tag{20}$$

Where ∂ equals to 0.1 and the value of ω is 0.5. $P_{\max_j}$ and $P_{\min_j}$ define the maximum and minimum values of i-th item. $r \in [-1, 1]$, $r_{1,2} \in [0, 1]$. In addition, $c_{1,2} = 1.5$. Thus, Eq. (21) updates the position of each particle.

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{21}$$

This updating is computed repeatedly until $\left|P_{gb_j}(t+1) - P_{gb_j}(t)\right| < \epsilon$. In the iteration where the condition is met, the process is stopped and the positions from the last iteration are averaged. The alternatives are ranked according to this average position.

4. Analysis

The evaluation results of the investment alternatives for floating renewable energy systems with the suggested technique are presented under subheadings.

4.1. Detecting the relevant Dec. Mkr. information using the information gain-based attribute selection

In the selection of Dec. Mkr.s., communication is established with managers and decision makers of companies working in the field of floating renewable energy. Interviews are held with managers who respond positively. The main issue that is taken into consideration in this process is that the manager has managed or is managing projects in this field. In addition, he/she has at least 10 years of experience in the field of floating renewable energy. Managers who meet these conditions are determined as Dec. Mkr.

Eight Dec. Mkr.s are determined for the study. However, since working with a large number of Dec. Mkr.s creates some problems, the most appropriate Dec. Mkr.s need to be determined objectively. In this context, the model requires that the education, experience, age and income of the Dec. Mkr.s are defined as inputs. The criteria determined for floating renewable energy systems also constitute the output variables. Accordingly, Table A1 summarizes the information of eight Dec. Mkr.s and their initial assessments of the criteria. Eq. (1) is used, and the Ɛ value of each criterion is calculated. Table A2 shows the Ɛ value of the criteria. Afterwards, the Ɛ values of criteria split by Dec. Mkr. information are calculated. Eq. (2) is used for the ▯ values. Table A3 shares the results according to Dec. Mkr.s information for STDR. According to Table A3, experience has highest ▯ value for STDR. Similarly, ▯ values are computed for other criteria. Table 1 displays the results for other criteria.

As can be seen Table 1, experience is highest value for STRD and ENVINT. While education is the most important for SPCOPT, salary and age are the best information for DSTEFF. According to the results, the most relevant Dec. Mkr.s are selected based on ▯ rules. The rules are created regarding to the highest positive scales for the most Dec. Mkr.s information. For example, since over 21 years of experience had the highest positive rating in the initial Dec.Mkr. review for STDR and ENVINT, these Dec. Mkr.s are selected for the most relevant Dec. Mkr. group for STDR and ENVINT. As a result of this rule sequence, the method process continues with the evaluations of the second, first and third Dec. Mkr.s. In other words, evaluations from the first three Dec. Mkr.s are collected, and evaluation matrices are constructed.

4.2. Creating the balanced evaluation matrices using Q-learning

Dinçer et al. [15,14] conducted an analysis on green hydrogen production using the Q-learning model, one of the decision-making models. Similarly, Dinçer et al. [16] conducted an analysis on corporate environmental investments using the same model. The evaluations from the most suitable Dec. Mkr.s determined in the previous step are collected and balanced in this sub-section. The alternatives evaluated in this process are offshore wind farms (OFFSHORE), hydrogen production stations (HYDST), grid support systems (GRIDSS), wave energy converters (WAVEC) and tidal energy systems (TES). Dec. Mkr.s evaluate both the dependency among the criteria and the criteria status of the alternatives using 5-scales. Table A4 summarizes the evaluations. According to these scales, N is (.2,.7,.1), L is (.4,.5,.1), M is (.6,.3,.1), S is (.8,.15,.05) and H is (.95,.05,.0).

Then, the total number of their relevant information is considered to determine the most experienced Dec. Mkr. Accordingly, Accordingly, the weights of the second, first and third Dec. Mkr.s are 0.571, 0.286 and 0.143, respectively. Because the second Dec. Mkr. with the most relevant information has 4 information. Thus, the most experienced Dec. Mkr. is the second Dec. Mkr. Then, the linguistic terms are converted to MFN numbers and Eq. (3) is used. Thus, the $\mathscr{R}_{s,a}$ of the evaluation matrices are calculated. Here, the weights of other Dec. Mkr.s are used as the r. Table A5 illustrates the $\mathscr{R}_{s,a}$ of the evaluation matrices.Similarly, Eq. (4) is used. Thus, the $\mathscr{P}_{s,a}$of the evaluation matrices are computed. Here, the weights of the second Dec. Mkr. are used as the p. Table A6 exhibits the $\mathscr{P}_{s,a}$ of the evaluation matrices. Afterwards, Eq. (5) is used for updating the evaluation matrices. Table A7 shows the $Q_{s,a}^{updated}$ of the evaluation matrices for $\alpha = 0.1$. To obtain the final evaluation matrices, the maximum value of the absolute difference between the initial and updated elements must remain smaller than 0.02. Therefore, six iterations are performed, and the condition is satisfied. In this case, Table 2 shows the final balanced evaluation matrices.

4.3. Applying the cognitive maps-based MOPSO with MFS for assessments of floating renewable energy systems investment alternatives

First, the relation matrix is constructed. For this, Eq. (6) is used and the average of the elements of the first three matrices in Table 2 is calculated. Table A8 presents the averaged elements for relation matrix. Next, Eq. (7) is used for creating the vectors from the elements of relation matrix. Table A9 summarizes these vectors. After creating vectors from the elements of the relation matrix, the angle between the two vectors is computed. Eq. (8) presents the cosine value of the angle, while the value of the angle is determined by the inverse cosine function. In this case, Table A10 reports the angle between the two vectors created from the element of relation matrix. In the next step, these angles are normalized using the piecewise function in Eq. (9). Table A11 gives the results of f for relation vectors. Using the values in GS1, Eq. (10) is

Table 1
The results for other criteria.

Education												
	STDR			ENVINT			SPCOPT			DSTEFF		
	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯
PhD	.918	.939	.467	1.585	1.189	.717	.918	.594	1.156	.918	1.189	.717
Master	1.585			1.585			.000			1.585		
Bachelor	.000			.000			1.000			1.000		
Experience												
	STDR			ENVINT			SPCOPT			DSTEFF		
	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯
0–15	.000	.451	.954	.000	.857	1.049	.000	1.107	.643	.000	1.201	.704
16–20	.722			.971			1.371			1.522		
21-	.000			1.000			1.000			1.000		
Salary												
	STDR			ENVINT			SPCOPT			DSTEFF		
	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯
< 3000	.000	1.094	.311	.000	1.439	.467	.000	1.094	.656	.000	1.094	.811
3000–4000	1.459			1.918			1.459			1.459		
4000 <	.000			.000			.000			.000		
Age												
	STDR			ENVINT			SPCOPT			DSTEFF		
	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯	Ɛ	Overall Ɛ	▯
< 45	.811	.750	.656	1.500	1.344	.561	.811	.750	1.000	1.500	1.094	.811
45–50	.918			1.585			.918			.918		
50 <	.000			.000			.000			.000		

Table 2
The final balanced evaluation matrices.

Dec.Mkr. 2	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
SPCOPT	(.95,.05,.00)	(.80,.15,.05)	(.00,.00,.00)	(.95,.05,.00)
DSTEFF	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)
Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.86,.11,.03)
SPCOPT	(.80,.15,.04)	(.72,.21,.07)	(.00,.00,.00)	(.80,.15,.04)
DSTEFF	(.95,.05,.00)	(.80,.15,.05)	(.86,.11,.03)	(.00,.00,.00)
Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.95,.05,.00)
SPCOPT	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)	(.80,.15,.05)
DSTEFF	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)
Dec.Mkr. 2	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
HYDST	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
GRIDSS	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
WAVEC	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)	(.60,.30,.10)
TES	(.95,.05,.00)	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)
Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.89,.09,.02)	(.80,.15,.04)	(.80,.15,.04)	(.95,.05,.00)
HYDST	(.89,.09,.02)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
GRIDSS	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
WAVEC	(.80,.15,.04)	(.80,.15,.05)	(.80,.15,.04)	(.68,.24,.08)
TES	(.95,.05,.00)	(.95,.05,.00)	(.80,.15,.05)	(.89,.09,.02)
Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)	(.95,.05,.00)
HYDST	(.80,.15,.05)	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)
GRIDSS	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
WAVEC	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
TES	(.60,.30,.10)	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)

calculated. Then, Eq. (11) is used, and $\mathscr{n}$ are obtained. Table A12 shows the $\mathscr{n}$ values for GS1. After that, Eqs. (12) and (13) are used for iterative sigmoid function. The iteration process continues until two consecutive sigmoid values are equal. Table A13 summarizes the sigmoid results up to the sixth iteration. Since the sigmoid values in the fifth and sixth iterations are the same, the iteration is stopped, and Eq. (14) is used to calculate the criterion weights. According to $\mathscr{w}$ values in Table A13, the most important criterion is SPCOPT. After determining the criteria weights, the necessary steps for ranking the alternatives begin. the decision matrix is constructed. For this, Eq. (6) is used and the average of the elements of the last three matrices in Table 2 is computed. Table A14 presents the averaged elements for decision matrix. The values of Table A14 are multiplied by the criterion weight value of Table A13. Thus, after the weighted decision matrix is constructed, vectors are defined from the elements of this matrix. Eq. (15) is used, and Table A15 shows these vectors.

After creating vectors from the elements of the weighted decision matrix, the angle between the two vectors is computed. Eq. (16) presents the cosine value of the angle, while the value of the angle is determined by the inverse cosine function. In this case, Table A16 shares the angle between the two vectors created from the element of weighted decision matrix. In the next step, these angles are normalized using the piecewise function in Eq. (9). Table A17 presents the results of f for weighted decision matrix. Using the values in GS1, Eq. (17) is computed. Next, Eq. (18) is used, and ƒ are obtained. Table A18 displays the ƒ values for GS1. After that, Eqs. (19) - (21) are used for iterative state vector. The iteration process continues until the condition is met. Table 3 shares the results of positions.

After the condition is met and the iteration is completed, the average values of the positions are calculated. The average values of the positions of investments are obtained as 0.1375, 0.1141, 0.1138, 0.1381, and 0.1396 respectively. So, the ranking results are given in descending order as TES, WAVEC, OFFSHORE, HYDST, GRIDSS.

4.4. Comparative results

In the previous section, only results are given for GS1 and $\alpha = 0.1$. The biggest advantage of using molecular fuzzy numbers and Q-learning is that the results can be compared with different shapes and α. Table 4 summarizes all comparative results.

According to Table 4, the ranks of the investments for floating renewable energy systems are some. Different α values are used to test the consistency of the results, while different GS states are used to test the reliability of the results. The fact that the results are the same for all these different states indicates that the ranking is consistent and valid.

Moreover, the comparative analysis is performed with ARAS. Thus, the ranks of ARAS and MOPSO are examined. The results of two models are shown in Fig. 2.

According to ranks in Fig. 2, the ranks are the same.

Table 3
The iterative positions.

	OFFSHORE$((V_1)(1))$	HYDST$((V_2)(1))$	GRIDSS$((V_3)(1))$	WAVEC$((V_4)(1))$	TES$((V_5)(1))$	OFFSHORE$((P_1)(1))$	HYDST$((P_2)(1))$	GRIDSS$((P_3)(1))$	WAVEC$((P_4)(1))$	TES$((P_5)(1))$	$((P_{gb})(1))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
OFFSHORE		.009	−.002	.035	.033	.00	.11	.13	.09	.11	.13	-
HYDST	.051		−.001	.027	.063	.15	.00	.18	.15	.14	.18	-
GRIDSS	.026	−.001		.049	.039	.15	.18	.00	.13	.16	.18	-
WAVEC	.037	−.002	.024		.034	.09	.12	.11	.00	.09	.12	-
TES	.027	.019	.004	.039		.11	.09	.12	.10	.00	.12	-
	OFFSHORE $((V_1)(2))$	**HYDST** $((V_2)(2))$	**GRIDSS** $((V_3)(2))$	**WAVEC** $((V_4)(2))$	**TES** $((V_5)(2))$	**OFFSHORE** $((P_1)(2))$	**HYDST** $((P_2)(2))$	**GRIDSS** $((P_3)(2))$	**WAVEC** $((P_4)(2))$	**TES** $((P_5)(2))$	$((P_{gb})(2))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
OFFSHORE		.04	.00	.10	.07	.00	.13	.13	.15	.14	.13	.00
HYDST	.12		.00	.08	.14	.21	.00	.18	.20	.21	.18	.00
GRIDSS	.08	.00		.13	.10	.20	.18	.00	.21	.21	.18	.00
WAVEC	.10	.00	.06		.10	.15	.12	.14	.00	.14	.12	.00
TES	.06	.06	.00	.09		.13	.13	.12	.14	.00	.12	.00

Table 4
The comparative results.

$\alpha = 0.1$	GS1	GS2	GS3	GS4	GS5
OFFSHORE	3	3	3	3	3
HYDST	4	4	4	4	4
GRIDSS	5	5	5	5	5
WAVEC	2	2	2	2	2
TES	1	1	1	1	1
$\alpha = 0.5$	**GS1**	**GS2**	**GS3**	**GS4**	**GS5**
OFFSHORE	3	3	3	3	3
HYDST	4	4	4	4	4
GRIDSS	5	5	5	5	5
WAVEC	2	2	2	2	2
TES	1	1	1	1	1
$\alpha = 1$	**GS1**	**GS2**	**GS3**	**GS4**	**GS5**
OFFSHORE	3	3	3	3	3
HYDST	4	4	4	4	4
GRIDSS	5	5	5	5	5
WAVEC	2	2	2	2	2
TES	1	1	1	1	1

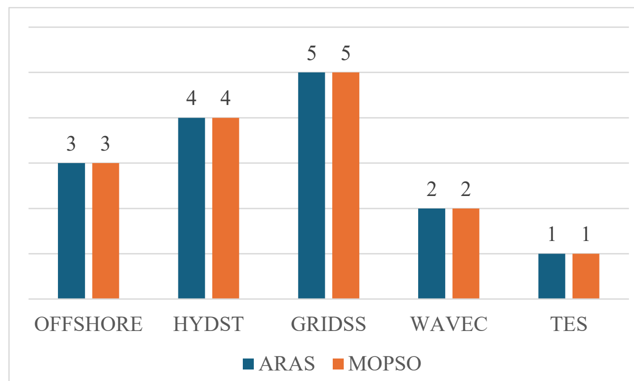

Fig. 2. The ranks of two models.

4.5. Sensitivity analysis

The analyses are repeated by making minimal changes in the criterion weights. Five different minimal changes in the criterion weights are made in this manuscript. Also, the ranking results are given by the selected and full expert groups. The results for these five changes and the different expert groups are given in Table 5.

Through molecular fuzzy logic and cognitive mapping, the complex interdependencies between criteria are assessed. The modeling process, which included 5 different geometric states (GS1–GS5), consistently ranked space optimization and environmental integration as top criteria under various configurations, indirectly validating their robustness. Also, comparative analysis and the sensitivity results with the different

Table 5
Sensitivity analysis.

Selected Expert Group (DM1, DM2, DM3)					
	SA1	**SA2**	**SA3**	**SA4**	**SA5**
OFFSHORE	3	3	3	3	3
HYDST	4	4	4	4	4
GRIDSS	5	5	5	5	5
WAVEC	2	2	2	2	2
TES	1	1	1	1	1
Full Expert Group (DM1, DM2, DM3, DM4, DM5, DM6, DM7, DM8)					
	SA1	**SA2**	**SA3**	**SA4**	**SA5**
OFFSHORE	3	3	3	3	3
HYDST	4	4	4	4	4
GRIDSS	5	5	5	5	5
WAVEC	2	2	2	2	2
TES	1	1	1	1	1

expert groups are coherent with different ranking methodologies. This consistency across configurations acts as a form of sensitivity-supported empirical reinforcement, aligning with literature-based examples.

We also added several real-world examples to demonstrate how these criteria critically affect floating renewable energy projects. For example, O'Shea et al. [40] and Manolache & Andrei [33] reported the integration of floating wind farms with aquaculture and maritime operations, highlighting the space-efficiency and multifunctionality of these platforms. Similarly, Chen et al. [6,7] demonstrated that deploying floating photovoltaics in the Yellow River region reduced reliance on hydropower while better preserving aquatic ecosystems, validating the significance of environmental integration. These cases provide practical evidence supporting our model's prioritization.

5. Discussion

Floating power generation systems are affected by and can affect the systems around them in many ways. Floating systems are suitable for generating energy in densely populated, space-constrained areas. These systems aim to produce clean energy in line with the decarbonization demands of the global economy [3,4]. Floating energy systems to be installed on the high seas and oceans can be combined with aquaculture activities in addition to generating energy, enabling multiple uses. In this way, environmental degradation is prevented while preserving the underwater life cycle (Pena et al., 2024). Space optimization with multi-use potential is the most important criterion for increasing the effectiveness of floating energy systems investments. Indeed, O'Shea et al. [40] stated that floating wind power plants can be used in combination with marine industrial activities. It is emphasized that this use contributes to global clean energy policy priorities and is important in terms of space and resource efficiency. Similarly, Chen et al. [6,7] underlined that offshore floating energy platforms serve industrial needs by using a single infrastructure. According to the study, using a floating energy system provides space saving and efficiency in aquaculture. Manolache and Andrei [33] pointed out that floating renewable energy platforms can be integrated into different areas such as tourism, transportation, water industry as well as energy production. In the study, it was stated that the multiple use of floating energy systems saves space and reduces costs. Lopes et al. [32] conducted studies on the electricity generation and efficiency of floating solar panel systems together with meteorological data, taking into account geographical references. In another study, [35] stated that it would be appropriate to place floating offshore wind panels close to the Irish coast in terms of energy efficiency and cost. In addition, Ikhennicheu et al. [28] reported that site selection is important in offshore energy systems. In the study, systems that require different technology should be installed in different water bodies such as sea and ocean.

Environmental integration with ecosystem protection is among the criteria for increasing the effectiveness of floating energy system investments. The establishment of floating systems by protecting underwater natural life cycles will not harm the ecological balance in energy production [46]. Garrod et al. [21] states that the energy production of floating systems should be organized in an environmentally sensitive manner. Also, Zhu et al. [53] stated that floating energy systems should be used to increase efficiency in aquaculture. Similarly, Chen et al. [6,7] stated that floating solar energy systems should take more place among renewable energy systems. The study also states that using floating solar energy to generate energy instead of hydroelectric power plants in China's Yellow River would be more beneficial for the river ecosystem.

In addition to important criteria for floating renewable system investments, one of the important alternatives is tidal energy systems. These systems have a significant potential in the field of renewable energy. Tidal energy is considered a reliable option among renewable energy sources due to its predictability [51]. Due to its predictability, it can be used as an efficient solution in areas with coastlines and strong tidal currents, but this system should be designed considering technical challenges and environmental factors [8]. Han et al. [24] stated that floating hybrid wind energy systems are complex systems. In addition, wind and wave conditions should be focused for the installation of these systems. This system is an important energy source in the world due to its features such as providing a continuous energy source, producing more dense energy, being used in areas far from the coast and zero carbon emission [49]. Lai et al. [30] proposed the use of energy converters integrated into floating energy systems for high energy conversion efficiency and effective wave frequency in the South China Sea. In the study, it is mentioned that the integrated wave energy converter will reduce the construction cost.

6. Conclusion

This study addresses a critical research gap by identifying and prioritizing the most significant determinants influencing floating renewable energy investments, using a novel and hybrid multi-stage decision-making framework. In this process, an innovative decision-making model is constructed via combining different techniques. The decision-making architecture uniquely integrates information gain, Q-learning, molecular fuzzy logic, and multi-objective particle swarm optimization (MOPSO), resulting in a robust, expert-adaptive, and uncertainty-aware model.

The model identified 'space optimization with multi-use potential' and 'environmental integration with ecosystem protection' as the most critical determinants, underscoring the need for multi-functional, ecologically sensitive design in marine energy projects. Tidal energy systems and wave energy converters emerged as the most strategic investment alternatives. These systems leverage the unique potential of water surfaces for energy generation while addressing the growing demand for sustainable and secure energy sources. This research contributes both theoretically and practically to the field of renewable energy by offering a structured criterion set for decision-makers and introducing novel methodologies.

While the study offers generalizable insights, it does not incorporate region-specific factors or real-time operational constraints. Future studies can enhance this model by incorporating dynamic sensor data, location-specific policy variables, or hybrid models combining expert-based and data-driven techniques. Additionally, further research may explore the scalability of the model to broader multi-energy systems and circular economy objectives. Another limitation of this study is that the analysis is based on expert opinion. This increases the subjectivity problem in the analysis process. In order to minimize this problem, an econometric analysis can be performed in future studies. It is possible to reach more objective analysis results by considering variables with numerical data.

Moreover, the study does not deeply consider the operational challenges. In the following studies, integrating real-time data and dynamic modelling techniques can improve the adaptability of the decision-making model. The model relies heavily on expert opinions for weighting and ranking factors. This situation can also be accepted another limitation of this study. To overcome this issue, a dynamic version of the model can be developed. Therefore, the importance of factors in real-time based on changing conditions can be updated. By bridging methodological innovation with actionable insights, this study supports the development of resilient, multifunctional, and sustainable floating energy infrastructures, a key component of global decarbonization and blue economy strategies.

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.

Acknowledgements

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

Appendix

Table A1
The Input-Output Variables of Model

Dec.Mkr.s	Inputs				Outputs			
	Education	Experience (year)	Salary (USD)	Age	System's ability with structural durability (STDR)	Environmental integration with ecosystem protection (ENVINT)	Space optimization with multi-use potential (SPCOPT)	Distribution efficiency with grid infrastructure (DSTEFF)
Dec.Mkr. 1	PhD	22	4000	47	High (H)	High	Significant	High
Dec.Mkr. 2	PhD	24	4500	51	High	Significant (S)	High	Significant
Dec.Mkr. 3	PhD	18	3750	45	Significant	Moderate	Significant	High
Dec.Mkr. 4	Master	16	3000	42	Significant	Moderate	Moderate	High
Dec.Mkr. 5	Bachelor	18	2500	40	Significant	Low (L)	Moderate	Moderate
Dec.Mkr. 6	Master	15	3000	41	Moderate (M)	Significant	Moderate	Moderate
Dec.Mkr. 7	Master	19	3250	49	High	Low	Moderate	Low
Dec.Mkr. 8	Bachelor	20	3000	44	Significant	Low	Low	Low

Table A2
The Ɛ Value of the Criteria

	Probability Degrees					Ɛ Values
	N	L	M	S	H	
STDR	.000	.000	.125	.500	.375	1.406
ENVINT	.000	.375	.250	.250	.125	1.906
SPCOPT	.000	.125	.500	.250	.125	1.750
DSTEFF	.000	.250	.250	.125	.375	1.906

Table A3
The Results for STDR

Education								
	Probability Degrees					Ɛ	Overall Ɛ	▯
	N	L	M	S	H			
PhD	.000	.000	.000	.333	.667	.918	.939	.467
Master	.000	.000	.333	.333	.333	1.585		
Bachelor	.000	.000	.000	1.000	.000	.000		
Experience								
	Probability Degrees					Ɛ	Overall Ɛ	▯
	N	L	M	S	H			
0–15	.000	.000	1.000	.000	.000	.000	.451	.954
16–20	.000	.000	.000	.800	.200	.722		
21-	.000	.000	.000	.000	1.000	.000		
Salary								
	Probability Degrees					Ɛ	Overall Ɛ	▯
	N	L	M	S	H			
Less than 3000	.000	.000	.000	1.000	.000	.000	1.094	.311
3000–4000	.000	.000	.167	.500	.333	1.459		
More than 4000	.000	.000	.000	.000	1.000	.000		
Age								
	Probability Degrees					Ɛ	Overall Ɛ	▯
	N	L	M	S	H			
Ages below 45	.000	.000	.250	.750	.000	.811	.750	.656
Ages between 45 and 50	.000	.000	.000	.333	.667	.918		
Ages above 50	.000	.000	.000	.000	1.000	.000		

Table A4
The Evaluations

Dec.Mkr. 2	STDR	ENVINT	SPCOPT	DSTEFF	Dec.Mkr. 1	STDR	ENVINT	SPCOPT	DSTEFF	Dec.Mkr. 3	STDR	ENVINT	SPCOPT	DSTEFF
STDR		H	H	H	STDR		H	H	H	STDR		S	S	S
ENVINT	S		S	S	ENVINT	S		S	H	ENVINT	S		S	H
SPCOPT	H	S		H	SPCOPT	M	M		M	SPCOPT	S	H		S
DSTEFF	H	S	S		DSTEFF	H	S	H		DSTEFF	S	S	S	
Dec.Mkr. 2	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**	**Dec.Mkr. 1**	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**	**Dec.Mkr. 3**	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	H	H	H	H	OFFSHORE	S	M	M	H	OFFSHORE	H	S	H	H
HYDST	H	S	S	S	HYDST	S	S	S	S	HYDST	S	S	H	S
GRIDSS	S	S	S	S	GRIDSS	S	S	S	S	GRIDSS	H	H	H	H
WAVEC	H	S	H	M	WAVEC	M	S	M	S	WAVEC	S	S	S	S
TES	H	H	S	H	TES	H	H	S	S	TES	M	H	S	S

Tables A5
$\mathscr{R}_{s,a}$ of the Evaluation Matrices

Dec.Mkr. 2-Dec.Mkr. 1	STDR	ENVINT	SPCOPT	DSTEFF
STDR	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
ENVINT	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.04, −.03, −.01)
SPCOPT	(−.10,.07,.03)	(−.06,.04,.01)	(.00,.00,.00)	(−.10,.07,.03)
DSTEFF	(.00,.00,.00)	(.00,.00,.00)	(.04, −.03, −.01)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(−.02,.01,.01)	(−.02,.01,.01)	(−.02,.01,.01)
ENVINT	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.02, −.01, −.01)
SPCOPT	(−.02,.01,.01)	(.02, −.01, −.01)	(.00,.00,.00)	(−.02,.01,.01)
DSTEFF	(−.02,.01,.01)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(−.04,.03,.01)	(−.10,.07,.03)	(−.10,.07,.03)	(.00,.00,.00)
HYDST	(−.04,.03,.01)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
GRIDSS	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
WAVEC	(−.10,.07,.03)	(.00,.00,.00)	(−.10,.07,.03)	(.06, −.04, −.01)
TES	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(−.04,.03,.01)
Dec.Mkr. 2-Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.00,.00,.00)	(−.02,.01,.01)	(.00,.00,.00)	(.00,.00,.00)
HYDST	(−.02,.01,.01)	(.00,.00,.00)	(.02, −.01, −.01)	(.00,.00,.00)
GRIDSS	(.02, −.01, −.01)	(.02, −.01, −.01)	(.02, −.01, −.01)	(.02, −.01, −.01)
WAVEC	(−.02,.01,.01)	(.00,.00,.00)	(−.02,.01,.01)	(.03, −.02, −.01)
TES	(−.05,.04,.01)	(.00,.00,.00)	(.00,.00,.00)	(−.02,.01,.01)

Tables A6
$\mathscr{P}_{s,a}$ of the Evaluation Matrices

Dec.Mkr. 2-Dec.Mkr. 1	STDR	ENVINT	SPCOPT	DSTEFF
STDR	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
ENVINT	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(−.09,.06,.03)
SPCOPT	(.20, −.14, −.06)	(.11, −.09, −.03)	(.00,.00,.00)	(.20, −.14, −.06)
DSTEFF	(.00,.00,.00)	(.00,.00,.00)	(−.09,.06,.03)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(.09, −.06, −.03)	(.09, −.06, −.03)	(.09, −.06, −.03)
ENVINT	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(−.09,.06,.03)
SPCOPT	(.09, −.06, −.03)	(−.09,.06,.03)	(.00,.00,.00)	(.09, −.06, −.03)
DSTEFF	(.09, −.06, −.03)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.09, −.06, −.03)	(.20, −.14, −.06)	(.20, −.14, −.06)	(.00,.00,.00)
HYDST	(.09, −.06, −.03)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
GRIDSS	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
WAVEC	(.20, −.14, −.06)	(.00,.00,.00)	(.20, −.14, −.06)	(−.11,.09,.03)
TES	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.09, −.06, −.03)
Dec.Mkr. 2-Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.00,.00,.00)	(.09, −.06, −.03)	(.00,.00,.00)	(.00,.00,.00)
HYDST	(.09, −.06, −.03)	(.00,.00,.00)	(−.09,.06,.03)	(.00,.00,.00)
GRIDSS	(−.09,.06,.03)	(−.09,.06,.03)	(−.09,.06,.03)	(−.09,.06,.03)
WAVEC	(.09, −.06, −.03)	(.00,.00,.00)	(.09, −.06, −.03)	(−.11,.09,.03)
TES	(.20, −.14, −.06)	(.00,.00,.00)	(.00,.00,.00)	(.09, −.06, −.03)

Tables A7
$Q_{s,a}^{updated}$ of the Evaluation Matrices for $\alpha = 0.1$

Dec.Mkr. 2-Dec.Mkr. 1	STDR	ENVINT	SPCOPT	DSTEFF
STDR	(.00,.00,.00)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.81,.14,.05)
SPCOPT	(.92,.07,.01)	(.78,.16,.05)	(.00,.00,.00)	(.92,.07,.01)
DSTEFF	(.95,.05,.00)	(.80,.15,.05)	(.81,.14,.05)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
STDR	(.00,.00,.00)	(.94,.06,.00)	(.94,.06,.00)	(.94,.06,.00)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.81,.14,.05)
SPCOPT	(.94,.06,.00)	(.81,.14,.05)	(.00,.00,.00)	(.94,.06,.00)
DSTEFF	(.94,.06,.00)	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)
Dec.Mkr. 2-Dec.Mkr. 1	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.94,.06,.00)	(.92,.07,.01)	(.92,.07,.01)	(.95,.05,.00)
HYDST	(.94,.06,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
GRIDSS	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
WAVEC	(.92,.07,.01)	(.80,.15,.05)	(.92,.07,.01)	(.62,.29,.10)
TES	(.95,.05,.00)	(.95,.05,.00)	(.80,.15,.05)	(.94,.06,.00)
Dec.Mkr. 2-Dec.Mkr. 3	**STDR**	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.95,.05,.00)	(.94,.06,.00)	(.95,.05,.00)	(.95,.05,.00)
HYDST	(.94,.06,.00)	(.80,.15,.05)	(.81,.14,.05)	(.80,.15,.05)
GRIDSS	(.81,.14,.05)	(.81,.14,.05)	(.81,.14,.05)	(.81,.14,.05)
WAVEC	(.94,.06,.00)	(.80,.15,.05)	(.94,.06,.00)	(.61,.29,.10)
TES	(.93,.07,.01)	(.95,.05,.00)	(.80,.15,.05)	(.94,.06,.00)

Table A8
The Averaged Elements for Relation Matrix

	STDR	ENVINT	SPCOPT	DSTEFF
STDR	(.00,.00,.00)	(.90,.08,.02)	(.90,.08,.02)	(.90,.08,.02)
ENVINT	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)	(.87,.10,.03)
SPCOPT	(.85,.12,.03)	(.82,.14,.04)	(.00,.00,.00)	(.85,.12,.03)
DSTEFF	(.90,.08,.02)	(.80,.15,.05)	(.82,.14,.04)	(.00,.00,.00)

Table A9
The Vectors from Elements of Relation Matrix

	Vectors
u_1	[(.90,.08,.02), (.90,.08,.02), (.90,.08,.02)]
u_2	[(.80,.15,.05), (.80,.15,.05), (.87,.10,.03)]
u_3	[(.85,.12,.03), (.82,.14,.04), (.85,.12,.03)]
u_4	[(.90,.08,.02), (.80,.15,.05), (.82,.14,.04)]

Table A10
The Angles Between the Two Vectors (Relation Matrix)

	θ_{u_1}	θ_{u_2}	θ_{u_3}	θ_{u_4}
θ_{u_1}		.091	.062	.086
θ_{u_2}	.091		.047	.094
θ_{u_3}	.062	.047		.052
θ_{u_4}	.086	.094	.052	

Table A11
The Results of F for Relation Vectors

GS1	$f(\theta_{u_1})$	$f(\theta_{u_2})$	$f(\theta_{u_3})$	$f(\theta_{u_4})$
$f(\theta_{u_1})$	.000	.029	.020	.027
$f(\theta_{u_2})$	.029	.000	.015	.030
$f(\theta_{u_3})$	.020	.015	.000	.017
$f(\theta_{u_4})$	.027	.030	.017	.000
GS2	$f(\theta_{u_1})$	$f(\theta_{u_2})$	$f(\theta_{u_3})$	$f(\theta_{u_4})$
$f(\theta_{u_1})$	.000	.043	.030	.041
$f(\theta_{u_2})$	.043	.000	.022	.045

(continued on next page)

Table A11 (*continued*)

GS1	$\boldsymbol{f(\theta_{u_1})}$	$\boldsymbol{f(\theta_{u_2})}$	$\boldsymbol{f(\theta_{u_3})}$	$\boldsymbol{f(\theta_{u_4})}$
$f(\theta_{u_3})$	.030	.022	.000	.025
$f(\theta_{u_4})$	.041	.045	.025	.000
GS3	$\boldsymbol{f(\theta_{u_1})}$	$\boldsymbol{f(\theta_{u_2})}$	$\boldsymbol{f(\theta_{u_3})}$	$\boldsymbol{f(\theta_{u_4})}$
$f(\theta_{u_1})$	.000	.048	.032	.045
$f(\theta_{u_2})$	.048	.000	.025	.049
$f(\theta_{u_3})$	.032	.025	.000	.027
$f(\theta_{u_4})$	.045	.049	.027	.000
GS4	$\boldsymbol{f(\theta_{u_1})}$	$\boldsymbol{f(\theta_{u_2})}$	$\boldsymbol{f(\theta_{u_3})}$	$\boldsymbol{f(\theta_{u_4})}$
$f(\theta_{u_1})$	.000	.050	.034	.047
$f(\theta_{u_2})$	.050	.000	.026	.051
$f(\theta_{u_3})$	.034	.026	.000	.029
$f(\theta_{u_4})$	.047	.051	.029	.000
GS5	$\boldsymbol{f(\theta_{u_1})}$	$\boldsymbol{f(\theta_{u_2})}$	$\boldsymbol{f(\theta_{u_3})}$	$\boldsymbol{f(\theta_{u_4})}$
$f(\theta_{u_1})$	.000	.058	.039	.055
$f(\theta_{u_2})$	.058	.000	.030	.060
$f(\theta_{u_3})$	.039	.030	.000	.033
$f(\theta_{u_4})$	.055	.060	.033	.000

Table A12
$\mathscr{n}$ Values for GS1

	STDR	ENVINT	SPCOPT	DSTEFF
STDR	0	.122	.180	.129
ENVINT	.122	0	.237	.119
SPCOPT	.180	.237	0	.213
DSTEFF	.129	.119	.213	0

Table A13
The Values of Sigmoid Function for GS1

	Sigmoid^{1}	***Sigmoid***^{2}	***Sigmoid***^{3}	***Sigmoid***^{4}	***Sigmoid***^{5}	***Sigmoid***^{6}	$\mathscr{w}$
STDR	.606	.568	.563	.562	.562	.562	.246
ENVINT	.617	.575	.569	.568	.568	.568	.249
SPCOPT	.652	.595	.589	.588	.588	.588	.257
DSTEFF	.613	.572	.567	.566	.566	.566	.248

Table A14
The Averaged Elements for Decision Matrix

	STDR	**ENVINT**	**SPCOPT**	**DSTEFF**
OFFSHORE	(.93,.06,.01)	(.85,.12,.03)	(.90,.08,.01)	(.95,.05,.00)
HYDST	(.88,.10,.02)	(.80,.15,.05)	(.85,.12,.03)	(.80,.15,.05)
GRIDSS	(.85,.12,.03)	(.85,.12,.03)	(.85,.12,.03)	(.85,.12,.03)
WAVEC	(.85,.12,.03)	(.80,.15,.05)	(.85,.12,.03)	(.69,.23,.08)
TES	(.83,.13,.03)	(.95,.05,.00)	(.80,.15,.05)	(.88,.10,.02)

Table A15
The Vectors from Elements of Weighted Decision Matrix

	Vector
y_1	[(.23,.02,.00), (.21,.03,.01), (.23,.02,.00), (.24,.01,.00)]
y_2	[(.22,.02,.01), (.20,.04,.01), (.22,.03,.01), (.20,.04,.01)]
y_3	[(.21,.03,.01), (.21,.03,.01), (.22,.03,.01), (.21,.03,.01)]
y_4	[(.21,.03,.01), (.20,.04,.01), (.22,.03,.01), (.17,.06,.02)]
y_5	[(.20,.03,.01), (.24,.01,.00), (.21,.04,.01), (.22,.02,.01)]

Table A16
The Angles Between the Two Vectors (Weighted Decision Matrix)

	θ_{y_1}	θ_{y_2}	θ_{y_3}	θ_{y_4}	θ_{y_5}
θ_{y_1}		.095	.075	.168	.123
θ_{y_2}	.095		.053	.078	.128
θ_{y_3}	.075	.053		.113	.082
θ_{y_4}	.168	.078	.113		.168
θ_{y_5}	.123	.128	.082	.168	

Table A17
The Results of F for Weighted Decision Matrix

GS1	$f(\theta_{y_1})$	$f(\theta_{y_2})$	$f(\theta_{y_3})$	$f(\theta_{y_4})$	$f(\theta_{y_5})$
$f(\theta_{y_1})$	.000	.030	.024	.054	.039
$f(\theta_{y_2})$	.030	.000	.017	.025	.041
$f(\theta_{y_3})$	.024	.017	.000	.036	.026
$f(\theta_{y_4})$	.054	.025	.036	.000	.054
$f(\theta_{y_5})$	.039	.041	.026	.054	.000
GS2	$f(\theta_{y_1})$	$f(\theta_{y_2})$	$f(\theta_{y_3})$	$f(\theta_{y_4})$	$f(\theta_{y_5})$
$f(\theta_{y_1})$	.000	.045	.036	.080	.059
$f(\theta_{y_2})$	.045	.000	.025	.037	.061
$f(\theta_{y_3})$	.036	.025	.000	.054	.039
$f(\theta_{y_4})$	.080	.037	.054	.000	.080
$f(\theta_{y_5})$	.059	.061	.039	.080	.000
GS3	$f(\theta_{y_1})$	$f(\theta_{y_2})$	$f(\theta_{y_3})$	$f(\theta_{y_4})$	$f(\theta_{y_5})$
$f(\theta_{y_1})$	.000	.050	.039	.088	.064
$f(\theta_{y_2})$	.050	.000	.028	.041	.067
$f(\theta_{y_3})$	.039	.028	.000	.059	.043
$f(\theta_{y_4})$	.088	.041	.059	.000	.088
$f(\theta_{y_5})$	.064	.067	.043	.088	.000
GS4	$f(\theta_{y_1})$	$f(\theta_{y_2})$	$f(\theta_{y_3})$	$f(\theta_{y_4})$	$f(\theta_{y_5})$
$f(\theta_{y_1})$	.000	.052	.041	.092	.067
$f(\theta_{y_2})$	.052	.000	.029	.042	.070
$f(\theta_{y_3})$	.041	.029	.000	.062	.045
$f(\theta_{y_4})$	.092	.042	.062	.000	.092
$f(\theta_{y_5})$	.067	.070	.045	.092	.000
GS5	$f(\theta_{y_1})$	$f(\theta_{y_2})$	$f(\theta_{y_3})$	$f(\theta_{y_4})$	$f(\theta_{y_5})$
$f(\theta_{y_1})$	.000	.061	.048	.107	.078
$f(\theta_{y_2})$	.061	.000	.034	.049	.081
$f(\theta_{y_3})$	.048	.034	.000	.072	.052
$f(\theta_{y_4})$	.107	.049	.072	.000	.107
$f(\theta_{y_5})$	.078	.081	.052	.107	.000

Table A18
f Values for GS1

	OFFSHORE	HYDST	GRIDSS	WAVEC	TES
OFFSHORE		.101	.128	.057	.078
HYDST	.101		.181	.123	.075
GRIDSS	.128	.181		.085	.116
WAVEC	.057	.123	.085		.057
TES	.078	.075	.116	.057	

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