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Enhancing decentralized energy storage investments with artificial intelligence-driven decision models

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Abstract
Decentralized energy storage investments play a crucial role in enhancing energy efficiency and promoting renewable energy integration. However, the complexity of these projects and the limited resources of the companies make it necessary to determine strategic priorities. This paper tries to define effective investment strategies for the improvements of the decentralized energy storage projects. In the first stage, the selection of mass experts is made via information gain-based mass expert selection. Next, the assessments of the experts are balanced based on the opinion of the best expert by using q-learning algorithm. Moreover, determinants of decentralized energy storage investments are examined with molecular fuzzy (MF) cognitive maps. Finally, strategy alternatives for decentralized energy storage investments are ranked with MF multi-objective particle swarm optimization (MOPSO). The main contribution of this study is the identification of the most effective decentralized energy storage investment alternatives by establishing a novel model. The main novelty of the proposed model is that considering information gain-based mass expert selection technique allows for higher consistency and decision efficiency. Owing to this issue, the decision-making process is accelerated, and the applicability of the results increases. The findings indicate that customer expectations (weight: 0.2577) and financial issues (weight: 0.2513) are the most essential criteria in improving the performance of decentralized energy storage investments. Furthermore, hydrogen-based energy storage (average value: 0.1878) and distributed battery swapping stations (average value: 0.1877) are the most important decentralized energy storage investment alternatives.

Keywords Decentralized energy storage · Energy investments · Energy efficiency · q-learning · Molecular fuzzy sets

1 Introduction

Decentralized energy storage investments are projects that indicate that the storage process of the produced energy is carried out in a local, distributed structure instead of a centralized system. In centralized energy storage systems, energy is usually produced in large-scale

Extended author information available on the last page of the article power plants. The produced energy is kept in a large central storage facility. In decentralized systems, energy production is carried out in places close to the point of consumption. In other words, these systems indicate that the storage of energy is carried out independently of the center, at a local level (Sharma et al. 2024). Decentralized energy storage investments are very important in terms of achieving sustainable development goals. With the development of these projects, it is possible to make the energy supply continuous. With the help of this situation, it is easier to increase the use of renewable energy. On the other hand, in centralized energy systems, large-scale failures can affect the entire region (Aghdam et al. 2025). However, distributed energy storage systems store energy at a local level. Owing to this issue, these projects are more resistant to major interruptions.

Many different factors can affect the performance of decentralized energy storage investments. Financial variables can be taken into consideration in this process. Initial costs are quite high in these projects. Therefore, appropriate financing models are needed for these projects to be carried out effectively. In decentralized energy storage projects, customers are very important in the adoption of these investments. Reliability of the systems and user-friendly designs are the basic expectations of customers from these projects. Similarly, it is very important for customers that these systems are affordable (Liu et al. 2024). In addition to them, the effectiveness of decentralized energy storage systems depends on the efficiency of the processes within the system. The performance of energy storage units depends on the effectiveness of the battery technology used. In this process, the systems must be easy to maintain and have a long life. This situation increases performance by reducing operational costs. Furthermore, decentralized energy storage investments grow with investments in innovative technologies and human capital (Kiehbadroudinezhad et al. 2025). It is very necessary to train experts who can manage and optimize these systems. With the help of this condition, disruptions in the process can be intervened much more quickly.

It is necessary to determine the factors that have the greatest impact on the effectiveness of decentralized energy storage investments. The main reason for this is that resources are limited. This makes it difficult to correctly determine strategic priorities in energy investments. Directing resources to the right place increases the success rate of the investment. This makes it necessary to determine the most critical factors. Determining the most important factors also increases the effectiveness of risk management processes. Owing to this condition, problems in the process can be determined more clearly. This makes it easier to take the right measures against these risks. Knowing which factor is more important helps to develop strategies for the long-term success of projects. The limited number of studies in the literature determining the most important factors can be considered both a problem and a research deficiency. This situation can lead to uncertainties, especially in complex processes such as decentralized energy storage investments. The fact that these factors are not determined in the literature means the lack of a framework to guide investors.

The purpose of this study is to identify effective investment strategies for the improvements of the decentralized energy storage projects. A new model is generated for the evaluation of these investments that consist of four stages. Firstly, the selection of mass experts is carried out. Secondly, the assessments of the experts are balanced based on the opinion of the best expert via q-learning algorithm. Thirdly, the criteria selected for decentralized energy storage investments are prioritized by using molecular fuzzy cognitive maps. Finally, the alternatives for decentralized energy storage investments are ranked with MF multi-objective particle swarm optimization (MOPSO). In this study, some research questions can be created as detailed below.

(1) Which indicators of decentralized energy storage investments should be mainly taken into consideration?
(2) Which decentralized energy storage investment alternatives should be priorly implemented?

Since decentralized energy storage projects are complex and multidimensional, it is not clear which are the right strategic priorities. This uncertainty can lead to investment failure. Moreover, these projects often face significant challenges. For instance, resources are limited in energy storage investments. Because of this issue, wrong prioritization causes operational costs of companies to increase too much. Furthermore, reducing uncertainties in investments helps to identify risks at an early stage. Determining the most important factors also supports a more comprehensive analysis of these risks. Additionally, determining the right factors increases the long-term success of projects. There are limited studies in the literature on determining the most important factors and priority investment alternatives in decentralized energy storage investments. An innovative model that contributes to the literature should be created by filling this gap. This situation is one of the important motivations for the study. In the model to be developed, techniques suitable for the subject of the study should be preferred. Similarly, to minimize the uncertainty in the analysis process, appropriate fuzzy numbers should be integrated into these techniques. The main novelty of the study is the development of a new model used to determine strategic priorities in decentralized energy storage investments. This ensures more efficient use of resources and a more solid basis for investment decisions.

The main contribution of this study is the identification of the most effective decentralized energy storage investment alternatives by establishing a novel model. This proposed model has some advantages in comparison with the previous ones. (1) The study obtains opinions from 8 experts. This number of experts is quite high for decision-making analysis. Therefore, the information gain-based mass expert selection technique reduces the number of experts from 8 to 3. In this process, the most effective experts are selected by the help of artificial intelligence implementations. In the literature, decision-making models generally consider the opinions of all experts with equal weight (Rahadian et al. 2024). Artificial intelligence-based mass expert selection technique enables the selection of the most effective experts (Yüksel et al. 2025). This allows for higher consistency and decision efficiency. Moreover, the high number of experts causes an increase in inconsistencies between opinions. The decision-making process needs to be simplified with a small number of but effective experts. The number of experts is reduced by using this artificial intelligence technique (Shahbaz et al. 2025). Owing to this issue, the decision-making process is accelerated, and the applicability of the results increases. A large number of experts can increase inconsistencies and biases arising from different expertise levels and demographic characteristics (Zhu et al. 2024). In this model, these inconsistencies can be reduced by selecting the most effective experts. This situation provides a more objective result (Yang et al. 2025a). (2) In the study, new fuzzy numbers called molecular fuzzy set are being developed. In this process, molecular geometry and fuzzy logic approaches are being integrated. Thanks to these new sets, data is normalized more successfully. This is especially important in terms of determining the weights of the criteria correctly in multi-criteria decision-making models. Thanks to molecular geometry, data is normalized in a more balanced and consistent way. This increases the reliability of the analysis processes. In addition to them, molecular fuzzy setter allows for the minimization of uncertainties. Traditional fuzzy approaches are powerful in modeling uncertainty (Wang et al. 2024; Santiago and Bedregal 2024). On the other hand, these sets may not be able to sufficiently reduce uncertainties in complex systems. These new sets significantly contribute to the solution of this problem by integrating molecular geometry with fuzzy logic. Traditional fuzzy sets are often inadequate for complex, multi-dimensional decision-making problems (Alkan and Kahraman 2024). Molecular fuzzy sets use the power of molecular geometry to better manage this complexity. Moreover, traditional fuzzy sets are limited in modeling uncertainty and complexity (Hussain et al. 2024; Thakur et al. 2024). Molecular fuzzy sets allow for more effective management of uncertainty by integrating with molecular geometry. Distributed energy storage investments include multi-dimensional and dynamic processes. Molecular structures enable the model to produce more accurate results by capturing fine details in the data. Intuitionistic fuzzy sets reduce uncertainty by modeling membership and non-membership degrees (Garg et al. 2024). However, molecular fuzzy sets provide a more precise modeling thanks to molecular geometry integration. Owing to this situation, data losses can be minimized.

This study includes 6 different sections. The following section examines existing studies on energy storage investments, fuzzy decision-making models, and techniques for minimizing uncertainty. The third section introduces a novel four-stage model that integrates the q-learning algorithm, molecular fuzzy cognitive maps, and molecular fuzzy multi-objective particle swarm optimization. The fourth section presents the outcomes of applying the proposed methodology to decentralized energy storage investments. The fifth section interprets the analysis results, linking them to the study's objectives and existing literature. The final section summarizes the study's key findings, emphasizing the importance of prioritizing critical factors for the success of decentralized energy storage investments.

2 Literature review

Finance is one of the important criteria in improving the performance of decentralized energy storage investments. While decentralized energy systems are generally claimed to be environmentally friendly, efficient, durable, reliable and accessible and provide higher energy security, it can also be said that they bring with them some challenges. For example, while it is not yet clear whether they will be able to meet the increasing needs and high expectations for demand management and storage, financial access and cost-effective solutions need to be developed (Bögel et al. 2021). In other words, decentralized storage systems contribute to encouraging the development of local grids and increasing the flexibility of the energy system, while the European Union regulatory framework also encourages the use of small-scale decentralized electricity storage systems (Martins et al. 2020). Hunt et al. (Hunt et al. 2022) proposed Elevator Energy Storage Technology (LEST) as an innovative energy storage approach for a decentralized energy storage solution, while also showing that gravitational energy storage technologies are particularly interesting for long-term energy storage in systems with small energy storage demands. Considering that using centralized control strategies for decentralized energy storage to compensate wind power fluctuations can effectively improve the accuracy of control, Li et al. (2020) adopted a centralized control strategy to regulate and control the energy storage device to reduce the deviation caused by all wind power fluctuations.

Customer expectations and demand are another important issue in improving the performance of decentralized energy storage investments. Indeed, when it comes to decentralized storage, the effect of microgrid behavior on consumer behavior is important, while decentralized control methods have the advantage of providing reductions in consumer costs (Dousti et al. 2024). In addition, decentralized energy management focuses on optimization algorithms, community participation, and technoeconomic analysis, while customer adoption of energy storage technologies is also an important criterion in evaluating the performance of this system (Mohanty et al. 2024). Bazdar et al. (2023) presented an energy management study strategy developed to increase the use of adiabatic compressed air energy storage (A-CAES) system for decentralized applications, while this analysis aims to test the feasibility assessment approach for decentralized A-CAES integrated with renewable energy. Zakeri et al. (Zakeri et al. 2021) proposed energy storage policies offer a positive return on investment when pairing a battery with solar photovoltaic without the need for central coordination of decentralized energy storage or provision of auxiliary services with electricity storage in buildings, and the optimum storage size is seen to be important to maximize the profitability of solar photovoltaic battery energy storage systems. On the other hand, Samanta et al. (Samanta et al. 2024) stated that when electric vehicles in homes and charging stations are parked and not charged, all electric vehicles in a local area can be combined to form a decentralized energy storage system, and thus electric vehicle owners can earn money through participation in electricity markets.

Another important criterion for improving the performance of decentralized energy storage investments can be considered as the efficiency of internal processes. Because the improvement of internal processes in areas such as production, maintenance and data analysis provide a positive effect while also reducing energy losses. In other words, it means that it can play complementary roles in decentralized energy system balancing and thus facilitate the further growth of renewable energy in the energy mix (Laugs et al. 2024). In order to improve the consumption capacity of wind power plants and cope with the problems of high risk, high cost and low efficiency in traditional demand response, Zhu et al. (2023) considered the load characteristics of the internal process flow of high-load enterprises and the transaction framework of load collector, wind energy, high-load enterprises is established based on blockchain technology to fully ensure the transparency and openness of transactions. Govindan et al. (2023) provided an effective approach to determine the adoption barriers of blockchain technology-based platforms in the healthcare sector in terms of financial, customer, learning-growth and internal process in a clearer way from balanced scorecard perspectives using the weighted effect nonlinear indicator system (WINGS) method. Carayannis et al. (2022) aimed to determine the most critical elements affecting the performance of distributed energy projects with knowledge-oriented competencies. In this way, companies will be able to focus on more critical elements to ensure efficiency for distributed energy projects.

Learning and growth is another factor that plays a critical role in improving the performance of decentralized energy storage investments. While organizations' increasing their knowledge in this area directly affects investment performance, improving organizational learning also increases the potential for possible activities of people and organizations through increased business processes (Chandra and Kumar 2021). In addition, learning and growth provides information about research and development activities that will result in more effective distributed energy technologies, while it is the learning and growth perspective that expresses the necessary infrastructure for the long-term growth and development of an organization (Júnior et al. 2023). Rosa et al. (2020) argued that the transformation of the electricity sector towards a more diversified and sustainable electricity generation increases the importance of distributed generation, and for this purpose, they develop the use of a performance measurement system based on balanced scorecard principles. Due to the lack of a framework to measure the circularity performance of the firm, Sahu et al. (2023) aimed to develop a framework to measure performance in terms of circularity percentage. For this purpose, graph theory and matrix approach are used to measure performance based on a sustainable balanced scorecard such as process, customer, learning and growth, and financial as well as environmental and social perspectives.

The results of the literature review show that some criteria play a critical role in improving the performance of decentralized energy storage investments. In this context, criteria such as finance, customer expectations and demand, internal processes, learning and growth are emphasized. However, since it is not possible to improve more than one variable together, determining the most important variables is very important due to economic constraints. While it is observed that there are not enough studies in the literature that take this situation into account, this issue can be considered as an important gap in determining the most appropriate criteria for improving the performance of decentralized energy storage investments. To eliminate this gap, this study analyzes with a novel model and attempts to fill this gap in literature. In this model, firstly, the experts are balanced based on artificial intelligence-oriented q-learning algorithm. Q-learning considers a learning process based on rewards and punishments to select the best expert (Chen et al. 2025). This application initially assigns equal importance weight to each expert (Li et al. 2025). Then, the accuracy and consistency of the data from the experts are analyzed (Yang et al. 2025b). Finally, the algorithm selects the expert with the most reliability and highest knowledge contribution as the best. The next stage is related to the evaluation of the criteria for decentralized energy storage investments via molecular fuzzy cognitive maps. This approach helps to understand how various factors interact with each other (Shen et al. 2025). Cognitive maps consist of nodes and edges (Anwar et al. 2025). Nodes represent factors or criteria involved in the decision process. On the other side, edges show the relationship between factors (Nápoles et al. 2025). The final stage includes ranking of the alternatives by multi-objective particle swarm optimization. This technique aims to optimize multiple objective functions simultaneously (Singh et al. 2025). Particles search for the best solution in a given search space (Rashno and Fadaei 2025). Moreover, it optimizes two or more conflicting objective functions (Hao et al. 2025). Besides, it is based on the principle of Pareto optimality.

3 Methodology

Decentralized energy storage investments play a crucial role for the improvements of the renewable energy projects. Several factors can have an influence on the performance of decentralized energy storage investments. However, it is necessary to compute the most critical factors because of the limited financial sources of the companies. Therefore, a priority analysis should be conducted to find these variables. Decision-making models can be taken into consideration to reach this objective. However, there are some significant criticisms for the existing models. The main problems in this context are defined below. (1) In traditional multi-criteria decision-making models, different expert opinions are considered with the same coefficient. However, since the demographic information of each expert is different, this assumption does not reflect the truth. (2) Traditional decision-making methods are often based on the assumption of independence among criteria, whereas in the real-world criteria interact with each other. (3) Existing methods generally provide static analyses, whereas in long-term processes such as decentralized energy storage investments, the status of alternatives may change over time. (4) Wrong fuzzy set selection can directly increase the problem of not being able to manage uncertainty. Classical fuzzy sets express uncertainty only with one-way membership functions. This may be inadequate in areas such as energy investment where there is a high degree of uncertainty.

The proposed model for the evaluation of decentralized energy storage investments consists of four stages. In the first stage, the selection of mass experts is carried out. In the second stage, the assessments of the experts are balanced according to the opinion of the best expert. In the third stage, the criteria selected for decentralized energy storage investments are prioritized based on expert opinions. In the last stage, the alternatives for decentralized energy storage investments are ranked. In accordance with the purposes of this four-stage model, information gain-based mass expert selection, Q-learning algorithm for unbalanced expert evaluations, molecular fuzzy (*MF*) cognitive maps and MF-MOPSO methods are used, respectively. The mathematical details of these methods are presented in this section (Shen et al. 2024). In addition to the methods mentioned, fuzzy number sets are used for analysis. The reason for this is to analyze the linguistic uncertainty in expert evaluations and thus to obtain more accurate and realistic results. This proposed model is mainly designed to satisfy the common criticisms for the existing model as detailed below. (1) In this model, the weights of experts are determined by considering demographic differences with the q-learning algorithm. Thus, the opinions of more experienced or specialized people in the relevant field gain more weight. (2) Relationships between criteria can be analyzed using the molecular fuzzy cognitive maps approach. This allows for a more realistic evaluation. (3) Future changes in alternatives can be calculated with swarm optimization. The MOPSO algorithm can perform multi-objective optimization. With the help of this issue, it can be estimated how alternatives will perform in the future. (4) The reason for choosing MFSs (MFSs) from fuzzy number sets is that the set is based on molecular geometry shapes. Thus, normalization is performed according to different molecular geometry shapes and the results are compared. Thanks to this feature, the consistency and validity of the results can be checked. The flowchart of process is presented in Fig. 1.

Definition 1 Let U be a MFS in the universe of discourse S. Then, μ, v, π are the degrees of membership, non-membership and hesitancy, respectively, the MFS is satisfied in Eq. (1).

$$\widetilde{U} = \{u\,|\mu_U(u) + v_U(u) + \pi_U(u) = 1, u \in U\} \tag{1}$$

Definition 2 Let $\widetilde{U}_1 = (\mu_1, v_1, \pi_1)$ and $\widetilde{U}_2 = (\mu_2, v_2, \pi_2)$ be two MFSs. Then, the general operations are defined by Eqs. (2–6).

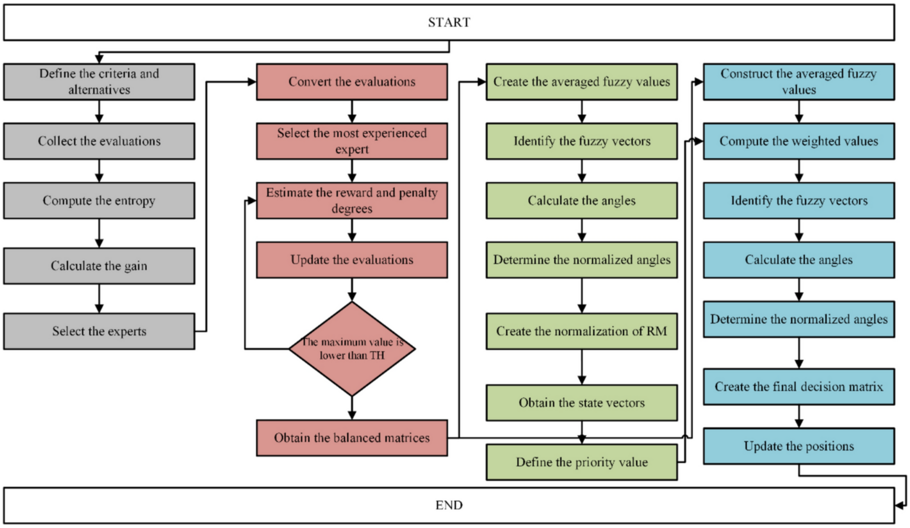

Fig. 1 The flowchart

$$\tilde{U}_1 \cup \tilde{U}_2 = \left\{\left(u, \max\left(\mu_{\tilde{U}_1}(u), \mu_{\tilde{U}_2}(u)\right), \min\left(\nu_{\tilde{U}_1}(u), \nu_{\tilde{U}_2}(u)\right), \min\left(\pi_{\tilde{U}_1}(u), \pi_{\tilde{U}_2}(u)\right)\right) u \in U\right\} \tag{2}$$

$$\tilde{U}_1 \cap \tilde{U}_2 = \left\{\left(u, \min\left(\mu_{\tilde{U}_1}(u), \mu_{\tilde{U}_2}(u)\right), \max\left(\nu_{\tilde{U}_1}(u), \nu_{\tilde{U}_2}(u)\right), \max\left(\pi_{\tilde{U}_1}(u), \pi_{\tilde{U}_2}(u)\right)\right) u \in U\right\} \tag{3}$$

$$\tilde{U}_1 \times \tilde{U}_2 = \left\{\left(u, \mu_{\tilde{U}_1}(u)\,\mu_{\tilde{U}_2}(u), \nu_{\tilde{U}_1}(u)\,\nu_{\tilde{U}_2}(u), \pi_{\tilde{U}_1}(u)\,\pi_{\tilde{U}_2}(u)\right) u \in U\right\} \tag{4}$$

$$c\tilde{U}_1 = \left\{\left(u, \min\left(c \cdot \mu_{\tilde{U}_1}(u), 1\right), \max\left(1 - c\left(1 - \nu_{\tilde{U}_1}(u)\right), 0\right), \max\left(1 - c\left(1 - \pi_{\tilde{U}_1}(u)\right), 0\right)\right) u \in U\right\} \tag{5}$$

$$\tilde{U}_1^c = \left\{\left(u, \left(\mu_{\tilde{U}_1}(u)\right)^c, 1 - \left(1 - \nu_{\tilde{U}_1}(u)\right)^c, 1 - \left(1 - \pi_{\tilde{U}_1}(u)\right)^c\right) u \in U\right\} \tag{6}$$

where c is positive number.

3.1 Information gain-based mass expert selection

In solving decision-making problems, selecting the appropriate expert plays a vital role, especially in issues that require high expertise. In the traditional approach, expert selection is based on subjective and limited factors. Therefore, it becomes difficult to standardize qualifications among expert groups. With this proposed model, an analysis based on information gain is performed to analyze the inputs of experts such as education, experience, salary and their initial evaluations on certain criteria as outputs. The model quantifies the effect of the experts' characteristics on the decision criteria by calculating the information-gain. As a result, the most relevant experts from the large number of experts are determined. The steps of information-based collective expert selection are summarized below.

Using the entropy measurement of each output, the expert choices of each output are utilized to quantify the uncertainty or disorder in the expert ratings of each criterion based on the initial expert judgments. This metric offers a starting point for assessing the degree to which certain expert qualities account for variability. The entropy of each output is computed with Eq. (7).

$$Entropy\,(OC) = -\sum_{i=1}^{n} pr_i \log_2 pr_i \tag{7}$$

where *OC* means the criterion in the output and *n* represents the level of the unique rating. The value of *pr* equals the probability of each rating in the expert dataset. Then, information gain is obtained for the input attribute that defines the expert specification. The information-gain is calculated using Eq. (8).

$$Gain\,(F, \mathrm{OC}) = Entropy\,(OC) - \sum_{f \in F} \frac{|OC_f|}{|OC|} Entropy\,(OC_f) \tag{8}$$

where OC_v refers the subset of output values when the dataset is split by features F having value *f*. While $|OC|$ means the total size of the dataset, $|OC_f|$ is the size of subset OC_f. Then, weighted entropy is estimated for each output. The weighted entropy value is obtained by the weights of the expert input in the total expert set. In this way, the overall entropy value provides the information gain value for the expert input on the selected expert output. Similarly, this calculation is applied to other expert features and outputs. Finally, the most suitable expert input with the maximum information gain value is selected for each criterion. In this way, the rule sequence that defines the most effective expert features is created.

3.2 Q-learning algorithm

Obtaining balanced expert evaluations is as effective as expert selection in solving the decision-making problem. Since the different experiences of the experts create differences in evaluations of the experts, the evaluation of the most experienced expert should be balanced with the evaluation of other experts. This algorithm is an iterative and reinforcement learning algorithm that serves this purpose. The steps of this algorithm for balancing expert evaluations are shared below (Fang et al. 2024).

First, the reward and penalty degrees between the most experienced expert and others are estimated for each state-action pair by Eqs. (9) and (10).

$$D_{r\,s,a} = f_r \times \left(Q_{s,a(mostExpert)} - Q_{s,a(otherExpert)}\right) \tag{9}$$

$$D_{p\,s,a} = f_p \times \left(Q_{s,a(otherExpert)} - Q_{s,a(mostExpert)}\right) \tag{10}$$

where $D_{r\,s,a}$ and $D_{p\,s,a}$ are reward and penalty degrees. f_r and f_p represent factors of reward and penalty, respectively. Afterwards, the updated Q values are calculated iteratively with learning rate by Eq. (11).

$$Q'_{s,a} = Q_{s,a(mostExpert)} + f_l \times \left(D_{r\,s,a} - D_{p\,s,a}\right) \tag{11}$$

where f_l is learning rate. The optimal evaluations are defined by Eqs. (12) and (13).

$$\delta_{s,a} = \left|Q'_{s,a} - Q_{s,a}\right| \tag{12}$$

$$\delta_{max} = \max_{s,a}\{\delta_{s,a}\} \tag{13}$$

Until δ_{max} is less than the threshold value, iterations are continued. The evaluations in the iteration where the convergence condition is accepted are considered as the final evaluations.

3.3 Normalization of MF decision matrix

Normalization of molecular fuzzy numbers (*MFN*) according to different molecular geometry shapes is used to compare analysis results. The normalization steps of the decision matrix consisting of MFN are detailed below.

Expert evaluations are transformed into MFN, averaged with the Eq. (14), and the molecular decision matrix is constructed. This matrix is shown in Eq. (15).

$$\widetilde{d}_{ij} = \left(\bigcup_{k=1}^{e}\widetilde{d}_k\right) = \left\{\left(u, \frac{1}{e}\sum_{k=1}^{e}\mu_{d_k}(u), \frac{1}{e}\sum_{k=1}^{e}v_{d_k}(u), \frac{1}{e}\sum_{k=1}^{e}\pi_{d_k}(u)\right) \mid u \in U\right\} \tag{14}$$

$$\widetilde{D} = \left[\widetilde{d}_{ij}\right]_{m\times n} \tag{15}$$

where $\widetilde{D}$ is the molecular decision matrix, $\widetilde{d}_{ij}$ means the MF elements of i-row of j-column of $\widetilde{D}$, *e* represents the number of experts. Later, the fuzzy vectors of MF decision matrix are determined for each row using Eq. (16).

$$\varphi_i = \left[(\mu_{i1}, v_{i1}, \pi_{i1}), (\mu_{i2}, v_{i2}, \pi_{i2}), \ldots (\mu_{it}, v_{it}, \pi_{it})\right] \tag{16}$$

where *t* is the length of the fuzzy vector. If the molecular decision matrix is a relation matrix, *t* is equal to *n-1* since the diagonal elements are excluded. Otherwise, *t* is equal to *n*. In this way, as many fuzzy vectors as there are rows are created. A fuzzy vector is multiplied with other fuzzy vectors using Eq. (17) and dot products are obtained.

$$(\varphi_i.\varphi_j) = \sum_{k=1}^{t}(\mu_{i,k}\cdot\mu_{j,k} + \nu_{i,k}\cdot\nu_{j,k} + \pi_{i,k}\cdot\pi_{j,k}) \tag{17}$$

Then, the angle between the fuzzy vectors is estimated by Eq. (18). For this calculation, cosine similarity and the magnitude of the fuzzy vectors are used.

$$\beta_{\varphi_i.\varphi_j} = cos^{-1}\left(\frac{(\varphi_i.\varphi_j)}{\left(\sum_{k=1}^{t}\left(\mu_{i,k}^2 + \nu_{i,k}^2 + \pi_{i,k}^2\right)\right).\left(\sum_{k=1}^{t}\left(\mu_{j,k}^2 + \nu_{j,k}^2 + \pi_{j,k}^2\right)\right)}\right) \tag{18}$$

where cos^{-1} is inverse cosine function. After the angles are calculated, the normalization of the angles according to different molecular geometry shapes is determined. Generally, normalized angle is divided by the maximum value of the angles. In addition, the normalized angles are calculated using the radians of the angles of molecular geometric shapes. The calculation formulation is given in Eq. (19).

$$normalize\left(\beta_{\varphi_i \cdot \varphi_j}\right) = \begin{cases} \frac{\beta_{\varphi_i \cdot \varphi_j}}{\beta_{max}}; generalcase \\ \frac{\beta_{\varphi_i \cdot \varphi_j}}{\pi}; linearshape \\ \frac{\beta_{\varphi_i \cdot \varphi_j}}{\frac{2\pi}{3}}; trigonalplanarshape \\ \frac{\beta_{\varphi_i \cdot \varphi_j}}{\frac{\pi}{2}}; tetrahedralshape \\ \frac{\beta_{\varphi_i \cdot \varphi_j}}{\frac{2\pi}{5}}; trigonalbipyramidalshape \\ \frac{\beta_{\varphi_i \cdot \varphi_j}}{\frac{\pi}{3}}; octahedralshape \end{cases} \tag{19}$$

where, β_{max} is the maximum value of angles. Afterwards, the reciprocals of the $normalize(\beta)$ are computed with the help of Eq. (20).

$$rv\left(\beta_{\varphi_i \cdot \varphi_j}\right) = \frac{1}{normalize\left(\beta_{\varphi_i \cdot \varphi_j}\right)} \tag{20}$$

Finally, the normalization of the decision matrix is defined by Eqs. (21) and (22).

$$\eta_{ij} = \frac{rv\left(\beta_{\varphi_i \cdot \varphi_j}\right)}{\sum_{j=1}^{n} rv\left(\beta_{\varphi_i \cdot \varphi_j}\right)} \tag{21}$$

$$\aleph = \left[\eta_{ij}\right] \tag{22}$$

3.4 MF-cognitive maps

Fuzzy cognitive maps are a multi-criteria decision-making technique developed to determine criteria priorities. The steps of calculating criteria priorities using MFN are explained below. First, expert evaluations are collected from selected experts and transformed into MFN. Then, the molecular relation matrix represented in Eq. (15) is constructed by averaging of evaluations with Eq. (14). After that, the normalization of the molecular relation matrix is obtained using the procedure introduced in Eqs. (16–22). This normalization matrix is $n \times n$ dimensional. After this step, the priorities of the criteria are calculated iteratively by the state vector process. For this purpose, the state vector values shown in Eq. (23) are estimated (Ouyang et al. 2024).

$$S\left(i\right) = \left[s_1\left(i\right), s_2\left(i\right), \ldots, s_n\left(i\right)\right] \tag{23}$$

where *S(0)* represents the initial state vector with values of 1. The value of i means the iteration number and *S(i)* is the activation levels at the i^{th} iteration. Thus, $s_n\left(i\right)$ equals to *n*th dimension vector in the number of *i* iteration. Next, the state vectors are updated iteratively with Eq. (24) until the results of two consecutive iterations are equal.

$$S\left(i+1\right)=\frac{1}{1+e^{-S(i)\cdot\aleph}} \tag{24}$$

Finally, the priorities of the criteria are found using Eq. (25).

$$pc_j=\frac{S\left(k\right)_j}{\sum_{j=1}^{n}S\left(k\right)_j} \tag{25}$$

where *S(k)* is the result of the state vectors at the final iteration.

3.5 MF-MOPSO

The MOPSO method, which is developed to rank the alternatives and also presents the relationship between the alternatives, is one of the multi-criteria decision-making techniques (Sotoudeh-Anvari 2020). This model provides balanced results in the research space by establishing pareto-optimal solutions for complex multi-objective decision-making problems. The integrated version with MFS is introduced below (Dinçer et al. 2024).

First, expert evaluations are collected from selected experts and transformed into MFN. Then, the molecular weighted decision matrix represented is constructed. The averaging evaluations are computed with Eq. (14) and after that, Eq. (26) is used for weighted values.

$$\widetilde{A}_{ij}=\left(pc_j\mu_{ij},pc_jv_{ij},pc_j\pi_{ij}\right) \tag{26}$$

After that, the normalization of the molecular decision matrix is obtained using the procedure introduced in Eqs. (16–22). This normalization matrix is $m\times n$ dimensional. This matrix is also the final decision matrix for this method. After the final decision matrix is constructed, the particle representation defined as a vector in Eq. (27) is created for the potential solutions in the decision matrix.

$$PR_i=\{pr_{i1},pr_{i2},\ldots,pr_{in}\} \tag{27}$$

where pr_{ij} represents the *j*th decision position of the *i*th particle and PR_i means the particle's initial position. Later, the particle's velocity is updated with the help of Eq. (28).

$$V_{ij}\left(t+1\right)=0.5\times V_{ij}\left(t\right)+c_{cognitive}r_1\left(P_{ij}\left(t\right)-PR_{ij}\left(t\right)\right)+c_{social}r_2\left(P_{gb_j}\left(t\right)-PR_{ij}\left(t\right)\right) \tag{28}$$

where $V_{ij}\left(t\right)$ means the volatility degree at the t^{th} iteration. $P_{ij}\left(t\right)$ is defined as the best position of each particle at the t^{th} iteration. $c_{cognitive}$ and c_{social} are the coefficients of cognitive and social and these coefficients are equal to 1.5. The random values of r_1 and r_2 are among 0 and 1. $P_{gb_j}\left(t\right)$ represents the global best position between the decision alternatives at the t^{th} iteration. It is determined as in Eq. (29), where $V_{ij}(1)$ is the initial velocity.

$$V_{ij}\left(1\right)=0.1\times\left(P_{max_i}-P_{min_i}\right)\times rn \tag{29}$$

where rn is any number between -1 and 1. After that, the updated position of each particle is computed by Eq. (30).

$$PR_{ij}(t+1) = PR_{ij}(t) + V_{ij}(t+1) \tag{30}$$

This update process continues until the condition in Eq. (31) is reached.

$$\left|P_{gb_j}(t+1) - P_{gb_j}(t)\right| < \epsilon \tag{31}$$

Finally, when the absolute difference in the global positions is very small, the averaged positions of the items are estimated by Eq. (32) for ranking.

$$\frac{1}{n}\sum_{i=1}^{n} P_{ij} \tag{32}$$

4 Analysis

The findings of the analysis for decentralized energy storage investments are shared in this section.

4.1 Detecting the relevant expert specifications using the information gain-based attribute selection

The information gain-based mass expert selection model is used to select the most appropriate expert for the analysis. First, individuals with expertise in decentralized energy storage investments are identified. The education, experience, salary and age information of the eight selected experts are determined as input. The evaluations of these eight experts on finance, customer, internal process and learning and growth criteria are identified as output. The input and output values of the eight experts are shared in Table 1.

Then, the entropies of the criteria are defined by Eq. (7). The entropies of the criteria are displayed in Table 2.

Table 1 Expert specifications and their initial criteria review

Experts	Inputs				Outputs			
	Education	Experience (year)	Salary ($)	Age	Finance	Customer	Internal process	Learning and growth
Expert 1	PhD	20	3000	45	High	High	Moderate	High
Expert 2	Master	16	3500	38	Significant	Significant	High	Significant
Expert 3	Bachelor	22	4000	53	Moderate	Significant	High	Significant
Expert 4	Master	13	2750	44	High	Significant	Significant	High
Expert 5	Bachelor	15	2500	42	Significant	Low	Low	Significant
Expert 6	PhD	18	3500	51	Low	Significant	Moderate	Moderate
Expert 7	Master	20	4000	48	High	Significant	Significant	High
Expert 8	PhD	21	4500	54	Significant	Low	Low	Moderate

Table 2 The entropy of the criteria

Linguistic Scales/Criteria	Probability degrees					Entropy values
	Negligible	Low	Moderate	Significant	High	
Finance	0	0.125	0.125	0.375	0.375	1.811
Customer	0	0.25	0	0.625	0.125	1.299
Internal Process	0	0.25	0.25	0.25	0.25	2.000
Learning and Growth	0	0	0.25	0.375	0.375	1.561

Table 3 The entropy values of finance split

Linguistic scales/educational degrees	Probability degrees					Entropy	Overall entropy	Information gain
	Negligible	Low	Moderate	Significant	High			
Education								
PhD	0.000	0.333	0.000	0.333	0.333	1.585	1.189	0.623
Master	0.000	0.000	0.000	0.333	0.667	0.918		
Bachelor	0.000	0.000	0.500	0.500	0.000	1.000		
Experience								
0–15	0.000	0.000	0.000	0.500	0.500	1.000	1.250	0.561
16–20	0.000	0.250	0.000	0.250	0.500	1.500		
21-	0.000	0.000	0.500	0.500	0.000	1.000		
Salary								
Less than 3000	0.000	0.000	0.000	0.500	0.500	1.000	1.451	0.360
3000–4000	0.000	0.200	0.200	0.200	0.400	1.922		
More than 4000	0.000	0.000	0.000	1.000	0.000	0.000		
Age								
Ages below 45	0.000	0.000	0.000	0.667	0.333	0.918	0.939	0.873
Ages between 45 and 50	0.000	0.000	0.000	0.000	1.000	0.000		
Ages above 50	0.000	0.333	0.333	0.333	0.000	1.585		

In the next step, the entropy values of criteria split by expert specifications are obtained. In addition, information gains are calculated using Eq. (8). The entropy values of finance split by expert specifications are illustrated in Table 3.

As seen in Table 3, the age information of eight experts has the highest information gain value in the expert specifications for the criterion of finance. So, it is seen that age has the most influential expert information for finance. Similarly, other entropy and information gain values are computed for the other criteria split by the inputs. Next, the information gain values for each input of the criteria are estimated. Thus, the gains for the expert specifications of the criteria are exhibited in Table 4.

According to information gain values in Table 4, age information is the biggest value for finance, salary has the most influential degree for customer, education is the best expert specification for the internal process, and education and age information have the most influential input equally for learning and growth.

In the other step, the most relevant experts from the group based on information gain rules are selected. The scales with the highest positive values are selected for the most

Table 4 The information gain values for the expert specifications of the criteria

	Finance			Customer			Internal process			Learning and growth		
Educational degrees	Entropy	Overall entropy	Information gain	Entropy	Overall entropy	Information gain	Entropy	Overall entropy	Information gain	Entropy	Overall entropy	Information gain
Education												
PhD	1.585	1.189	0.623	1.585	0.844	0.454	0.918	0.939	1.061	0.918	0.689	0.873
Master	0.918			0.000			0.918			0.918		
Bachelor	1.000			1.000			1.000			0.000		
Experience												
0–15	1.000	1.250	0.561	1.000	0.906	0.393	1.000	1.250	0.750	1.000	1.250	0.311
16–20	0.918			0.000			0.918			0.918		
21-	1.000			1.000			1.000			0.000		
Salary												
Less than 3000	1.000	1.451	0.360	1.000	0.701	0.598	1.000	1.201	0.799	1.000	1.201	0.360
3000–4000	1.922			0.722			1.522			1.522		
More than 4000	0.000			0.000			0.000			0.000		
Age												
Ages below 45	0.918	0.939	.873	0.918	0.939	0.360	1.585	1.439	0.561	0.918	0.689	0.873
Ages between 45 and 50	0.000			1.000			1.000			0.000		
Ages above 50	1.585			0.918			1.585			0.918		

influential expert specifications. For instance, the age between 45 and 50 years old has the highest positive assessment in the initial expert review for the finance. So, the experts with the age between 45 and 50 years old are selected for the most relevant expert group respect to finance. Similarly, the scales of the other most relevant expert inputs with the highest positive assessments are detected as salary between 3000$ and 4000$ for customer, the master's degree for internal process, the master's degree as well as age between 45 and 50 years old for learning and growth. Based on these information gain-based rules, the final most relevant expert group is determined as Expert 1 and 2 matching two inputs; Expert 3 with 3 relevant expert specifications. As Expert 3 has the highest priority with matching 3 inputs into the expert group, Expert 1 and Expert 2 have same value in the expert pool. Afterwards, the linguistic terms of the first three experts with five scales (negligible, low, moderate, significant and high) are collected for the relation and decision matrices.

4.2 Creating the balanced expert evaluations by Q-learning algorithms

A set of criteria is determined for decentralized energy storage investments. The preferred outputs for experts are finance (F), customer (C), internal process (IP) and learning and growth (LG). These four criteria are evaluated by the first three experts on a five-point scale. The experts' evaluations of the criteria relations are presented in Table 5.

Similarly, the decentralized energy storage investment alternatives are advanced battery technologies (ABT), hydrogen-based energy storage (HES), recycled EV batteries for stationary storage (REB), distributed battery swapping stations (DBS) and flywheel energy storage (FES). Evaluations of five investment alternatives by experts according to the criteria are illustrated in Table 6.

To apply the Q-learning algorithm, the most experienced expert must be determined. For this reason, the weights of the experts are computed by considering the total number of their relevant specifications. According to this situation, Expert 3 has the biggest weight with three relevant specifications of the four expert specifications. Next, the normalized weights are obtained and the normalized weights of the first, second and third experts are 0.286, 0.286 and 0.429, respectively. As can be seen from these normalized weight values, the best expert is the third expert. In other words, the evaluations of the third expert are the initial fuzzy Q matrix and the evaluations of other experts are compared pairwise with this evaluation after transforming expert evaluations into MFN. The weight of the third expert is used as the f_p, while the weights of the other experts are considered as the f_r.

The results of obtaining balanced expert evaluations of the relation matrix are introduced. A similar process is applied to the decision matrix. In the beginning of the Q-learning algorithm, Eq. (9) is used for calculating $D_{rs,a}$ of MF Q relation and decision matrices among the experts. The results for relation matrix are displayed in Table 7.

At the same time, Eq. (10) is used for computing $D_{p_{s,a}}$ of MF Q relation and decision matrices among the experts. The results for relation are exhibited in Table 8.

After obtaining the $D_{rs,a}$ and $D_{p_{s,a}}$, Eq. (11) is applied for a f_l of 0.1 and the $Q'_{s,a}$ of the matrices are constructed. The $Q'_{s,a}$ of MF Q relation matrix among the experts is shown in Table 9.

Next, the values of $\delta_{s,a}$ are calculated with Eq. (12). The threshold value is 0.02. When the value in Eq. (13) is greater than the threshold value, a decision is made to continue the

Table 5 The linguistic terms of the criteria

Expert 3	F	C	IP	LG
F		M	S	S
C	S		S	S
IP	H	H		M
LG	S	S	H	
Expert 1	**F**	**C**	**IP**	**LG**
F		M	M	S
C	S		S	S
IP	M	M		M
LG	S	S	H	
Expert 2	**F**	**C**	**IP**	**LG**
F		S	S	S
C	S		S	S
IP	H	H		S
LG	H	M	H	

Table 6 The linguistic terms of the alternative

Expert 3	F	C	IP	LG
ABT	S	H	H	H
HES	H	M	H	M
REB	S	S	S	S
DBS	M	M	H	M
FES	M	H	S	S
Expert 1	**F**	**C**	**IP**	**LG**
ABT	S	H	M	H
HES	H	M	M	M
REB	S	S	S	S
DBS	M	H	M	M
FES	H	H	S	S
Expert 2	**F**	**C**	**IP**	**LG**
ABT	H	H	H	H
HES	H	M	H	M
REB	H	H	H	H
DBS	M	M	H	M
FES	M	H	S	S

iteration. Accordingly, the first iteration is performed and the calculated absolute difference of MF Q relation between the experts are summarized in Table 10.

Some MFN in Table 10 is larger than the threshold value. For this reason, iteration continues until the $\delta_{s,a}$ remains below the threshold value. Later, the stability of the Q with the convergence test for relation and decision matrices is determined. So, the iterative $\delta_{s,a}$ of the MF relation matrix between First and Third Experts is summarized in Table 11.

The values of $\delta_{s,a}$ at the fifth iteration are lower than the threshold values for relation matrix among First and Third Experts. Finally, the stable MF values of experts for these matrices are obtained. The MF evaluations for relation matrix by the experts are exhibited in Table 12.

Table 7 The $D_{r_{s,a}}$ for relation matrix

Expert 3–expert 1	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(− 0.06, 0.04, 0.01)	(0.00, 0.00, 0.00)
C	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
IP	(− 0.10, 0.07, 0.03)	(− 0.10, 0.07, 0.03)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
LG	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
Expert 3–expert 2	**F**	**C**	**IP**	**LG**
F	(0.00, 0.00, 0.00)	(0.06, − 0.04, − 0.01)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
C	(0.00, 0.00, 0.00)	(0.00, .00, .00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
IP	(0.00, 0.00, 0.00)	(0.00, .00, .00)	(0.00, 0.00, 0.00)	(0.06, − 0.04, − 0.01)
LG	(0.04, − 0.03, − 0.01)	(− 0.06, 0.04, 0.01)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)

Table 8 The $D_{p_{s,a}}$ for relation matrix

Expert 3–expert 1	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.09, − 0.06, − 0.02)	(0.00, 0.00, 0.00)
C	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
IP	(0.15, − 0.11, − 0.04)	(0.15, − 0.11, − 0.04)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
LG	(0.00, .00, .00)	(0.00, 0.00, 0.00)	(0.00, 0.00,0.00)	(0.00, 0.00, 0.00)
Expert 3–expert 2	**F**	**C**	**IP**	**LG**
F	(0.00, 0.00, 0.00)	(− 0.09, 0.06, 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
C	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
IP	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(− 0.09, 0.06, 0.02)
LG	(− 0.06, 0.04, 0.02)	(0.09, − 0.06, − 0.02)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)

Table 9 The $Q'_{s,a}$ of relation matrix

Expert 3–expert 1	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)	(0.79, 0.16, 0.05)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.93, 0.07, 0.01)	(0.93, 0.07, 0.01)	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)
LG	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)
Expert 3–expert 2	**F**	**C**	**IP**	**LG**
F	(0.00, 0.00, 0.00)	(0.61, 0.29, 0.10)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)	(0.61, 0.29, 0.10)
LG	(0.81, 0.14, 0.05)	(0.79, 0.16, 0.05)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)

Similarly, the MF evaluations for decision matrix by the experts are illustrated in Table 13.

Table 10 The $\delta_{s,a}$ for relation at the first iteration

Expert 3-Expert 1	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.014,0.011,0.004)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.025,0.018,0.007)	(0.025,0.018,0.007)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
LG	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
Expert 3-Expert 2	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.014,0.011,0.004)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.014,0.011,0.004)
LG	(0.011,0.007,0.004)	(0.014,0.011,0.004)	(0.000,0.000,0.000)	(0.000,0.000,0.000)

Table 11 Iterative $\delta_{s,a}$ for Relation Matrix Among First and Third Experts

Iteration 2				
Expert 3-Expert 1	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.013,0.010,0.003)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.023,0.017,0.007)	(0.023,0.017,0.007)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
LG	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
Iteration 3				
Expert 3-Expert 1	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.012,0.009,0.003)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.022,0.015,0.006)	(0.022,0.015,0.006)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
LG	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
Iteration 4				
Expert 3-Expert 1	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.011,0.009,0.003)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.020,0.014,0.006)	(0.020,0.014,0.006)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
LG	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
Iteration 5				
Expert 3-Expert 1	F	C	IP	LG
F	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.011,0.008,0.003)	(0.000,0.000,0.000)
C	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
IP	(0.019,0.013,0.005)	(0.019,0.013,0.005)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
LG	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)

4.3 Prioritization the criteria using MF-cognitive maps

Using Eq. (14), the average of the values in Table 12 is calculated and the form in Eq. (15) is constructed. The averaged $\widetilde{Q}$ for the relation matrix is shown in Table 14.

Then, the rows of the MF relation matrix are defined as fuzzy vectors. Since the number of criteria is four and the diagonal objects are empty, the t value is 3. In this case, the fuzzy vectors expressed by Eq. (16) are displayed in Table 15.

Table 12 The $\widetilde{Q}$ for relation matrix

Expert 3	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)
LG	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)
Expert 1	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)	(0.74, 0.20, 0.07)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.84, 0.13, 0.03)	(0.84, 0.13, 0.03)	(0.00, 0.00, 0.00)	(0.60, 0.30, 0.10)
LG	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)
Expert 2	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)
LG	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)

Table 13 The $\widetilde{Q}$ for decision matrix

Expert 3	F	C	IP	LG
ABT	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
HES	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)
REB	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
DBS	(0.60, 0.30, 0.10)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)
FES	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
Expert 1	F	C	IP	LG
ABT	(0.80, 0.15, 0.05)	(0.95, 0.05, 0.00)	(0.84, 0.13, 0.03)	(0.95, 0.05, 0.00)
HES	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)	(0.84, 0.13, 0.03)	(0.60, 0.30, 0.10)
REB	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
DBS	(0.60, 0.30, 0.10)	(0.71, 0.22, 0.07)	(0.84, 0.13, 0.03)	(0.60, 0.30, 0.10)
FES	(0.71, 0.22, 0.07)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
Expert 2	F	C	IP	LG
ABT	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
HES	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)
REB	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)	(0.95, 0.05, 0.00)
DBS	(0.60, 0.30, 0.10)	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)
FES	(0.60, 0.30, 0.10)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)

Table 14 The averaged $\widetilde{Q}$ for the relation matrix

	F	C	IP	LG
F	(0.00, 0.00, 0.00)	(0.67, 0.25, 0.08)	(0.78, 0.17, 0.06)	(0.80, 0.15, 0.05)
C	(0.80, 0.15, 0.05)	(0.00, 0.00, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)
IP	(0.91, 0.08, 0.01)	(0.91, 0.08, 0.01)	(0.00, 0.00, 0.00)	(0.67, 0.25, 0.08)
LG	(0.85, 0.12, 0.03)	(0.73, 0.20, 0.07)	(0.95, 0.05, 0.00)	(0.00, 0.00, 0.00)

Table 15 φ for relation matrix

	MF vectors
φ_1	[(0.67, 0.25, 0.08), (0.78, 0.17, 0.06), (0.80, 0.15, 0.05)]
φ_2	[(0.80, 0.15, 0.05), (0.80, 0.15, 0.05), (0.80, 0.15, 0.05)]
φ_3	[(0.91, 0.08, 0.01), (0.91, 0.08, 0.01), (0.67, 0.25, 0.08)]
φ_4	[(0.85, 0.12, 0.03), (0.73, 0.20, 0.07), (0.95, 0.05, 0.00)]

Table 16 Dot Products of Fuzzy relation vectors

	φ_1	φ_2	φ_3	φ_4
φ_1		1.891	1.929	1.974
φ_2	1.891		2.061	2.087
φ_3	1.929	2.061		2.118
φ_4	1.974	2.087	2.118	

Table 17 β in radians for relation matrix

	$\beta_{\varphi 1}$	$\beta_{\varphi 2}$	$\beta_{\varphi 3}$	$\beta_{\varphi 4}$
$\beta_{\varphi 1}$		0.116	0.262	0.189
$\beta_{\varphi 2}$	0.116		0.175	0.138
$\beta_{\varphi 3}$	0.262	0.175		0.290
$\beta_{\varphi 4}$	0.189	0.138	0.290	

Since each row of the relation matrix represents a fuzzy vector, four fuzzy vectors are created. The dimension of the fuzzy vectors is three. Then, the dot product of these fuzzy vectors is calculated pairwise with the help of Eq. (17). The result of dot products of MF relation vectors is shared in Table 16.

Equation (18) is used to calculate the angle. Accordingly, the angle for relation matrix are illustrated in Table 17.

After the angles are obtained, the normalization of the angles is performed. For this, Eq. (19) is used, while the normalized angle relation values according to various shapes are summarized in Table 18.

Afterwards, Eq. (20) used for the values of $rv\left(\beta_{\varphi_i \cdot \varphi_j}\right)$. After that, the normalization of the relation is defined using the $rv\left(\beta_{\varphi_i \cdot \varphi_j}\right)$. For this, Eqs. (21) and (22) are used. The normalized values for linear shape is shared in Table 19.

After obtaining normalization of the MF relation matrix, Eqs. (23–25) are performed. In other words, the state vectors are calculated iteratively. When the results of two consecutive iterations are equal, the priorities of the criteria are determined. This situation occurs in the sixth iteration. The iterative state vectors and priority values for linear are summarized in Table 20.

Finally, the pc values are shown in Fig. 2.

As can be seen in Table 20, the values of S(6) and S(5) are the same. Due to this equality, the values in the sixth iteration are normalized and the criterion priorities are obtained. Because of the advantage of MFN, the results of different molecular geometry shapes can be compared. Accordingly, the comparative priority order of the criteria according to different molecular geometry shapes is shown in Table 21.

The consistency of the priority order of the criteria can be tested with different learning rates. The validity can be tested by comparing the priority order of the criteria accord-

Table 18 Normalized β Values according to Different Molecular Geometry Shapes

Linear	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})
Normalize(β_{φ_1})	0.000	0.037	0.083	0.060
Normalize(β_{φ_2})	0.037	0.000	0.056	0.044
Normalize(β_{φ_3})	0.083	0.056	0.000	0.092
Normalize(β_{φ_4})	0.060	0.044	0.092	0.000
Trigonal planar	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})
Normalize(β_{φ_1})	0.000	0.055	0.125	0.090
Normalize(β_{φ_2})	0.055	0.000	0.084	0.066
Normalize(β_{φ_3})	0.125	0.084	0.000	0.138
Normalize(β_{φ_4})	0.090	0.066	0.138	0.000
Tetrahedral	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})
Normalize(β_{φ_1})	0.000	0.061	0.137	0.099
Normalize(β_{φ_2})	0.061	0.000	0.092	0.072
Normalize(β_{φ_3})	0.137	0.092	0.000	0.152
Normalize(β_{φ_4})	0.099	0.072	0.152	0.000
Trigonal Bipyramidal	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})
Normalize(β_{φ_1})	0.000	0.063	0.143	0.103
Normalize(β_{φ_2})	0.063	0.000	0.096	0.075
Normalize(β_{φ_3})	0.143	0.096	0.000	0.158
Normalize(β_{φ_4})	0.103	0.075	0.158	0.000
Octahedral	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})
Normalize(β_{φ_1})	0.000	0.074	0.167	0.120
Normalize(β_{φ_2})	0.074	0.000	0.112	0.088
Normalize(β_{φ_3})	0.167	0.112	0.000	0.185
Normalize(β_{φ_4})	0.120	0.088	0.185	0.000

Table 19 The values of η for relation matrix according to linear shape

	F	C	IP	LG
F		0.253	0.112	0.155
C	0.253		0.167	0.213
IP	0.112	0.167		0.101
LG	0.155	0.213	0.101	

Table 20 The iterative state vectors and priority values for linear shape

	$S(0)$	$S(1)$	$S(2)$	$S(3)$	$S(4)$	$S(5)$	$S(6)$
F	1	0.627	0.581	0.575	0.574	0.574	0.574
C	1	0.653	0.596	0.590	0.589	0.589	0.589
IP	1	0.594	0.560	0.555	0.555	0.555	0.555
LG	1	0.615	0.573	0.568	0.567	0.567	0.567

Fig. 2 PC values

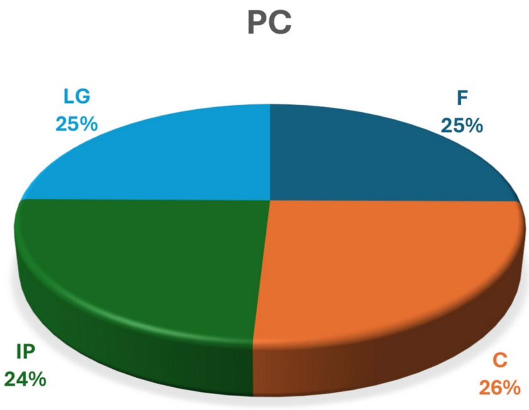

Table 21 The comparative priority orders of the criteria

Learning rate:.1	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
F	2	2	2	2	2
C	1	1	1	1	1
IP	4	4	4	4	4
LG	3	3	3	3	3
Learning rate:.5	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
F	2	2	2	2	2
C	1	1	1	1	1
IP	4	4	4	4	4
LG	3	3	3	3	3
Learning rate:1	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
F	2	2	2	2	2
C	1	1	1	1	1
IP	4	4	4	4	4
LG	3	3	3	3	3

ing to different molecular geometry shapes. According to all these cases, the results are valid and consistent because the priority order of the criteria is similar. Accordingly, the most important criterion for decentralized energy storage investments is the customer. The effectiveness of decentralized energy storage systems is directly related to the needs and consumption habits of users. In this context, if customer expectations are not analyzed correctly, the efficiency of the investment may decrease. Energy storage systems should allow flexible demand management by customers. Applications that can optimize customer energy consumption are preferred more. The implementation of effective pricing strategies is also of critical importance in this process. This situation provides very important benefits to customers. In this context, some applications that can increase customer satisfaction should be implemented. Customer feedback should be taken into consideration in this process. This situation supports the adaptation of applications to customer needs.

Table 22 The averaged $\widetilde{Q}$ for the decision matrix

	F	C	IP	LG
ABT	(0.85, 0.12, 0.03)	(0.95, 0.05, 0.00)	(0.91, 0.08, 0.01)	(0.95, 0.05, 0.00)
HES	(0.95, 0.05, 0.00)	(0.60, 0.30, 0.10)	(0.91, 0.08, 0.01)	(0.60, 0.30, 0.10)
REB	(0.85, 0.12, 0.03)	(0.85, 0.12, 0.03)	(0.85, 0.12, 0.03)	(0.85, 0.12, 0.03)
DBS	(0.60, 0.30, 0.10)	(0.64, 0.27, 0.09)	(0.91, 0.08, 0.01)	(0.60, 0.30, 0.10)
FES	(0.64, 0.27, 0.09)	(0.95, 0.05, 0.00)	(0.80, 0.15, 0.05)	(0.80, 0.15, 0.05)

Table 23 φ for decision matrix

Vectors	Fuzzy vectors
φ_1	[(0.21, 0.03, 0.01), (0.24, 0.01, .00), (0.22, 0.02, 0.00), (0.24, 0.01, 0.00)]
φ_2	[(0.24, 0.01, 0.00), (0.15, 0.08, 0.03), (0.22, 0.02, 0.00), (0.15, 0.07, 0.02)]
φ_3	[(0.21, 0.03, 0.01), (0.22, 0.03, 0.01), (0.21, 0.03, 0.01), (0.21, 0.03, 0.01)]
φ_4	[(0.15, 0.08, 0.03), (0.16, 0.07, 0.02), (0.22, 0.02, 0.00), (0.15, 0.07, 0.02)]
φ_5	[(0.16, 0.07, 0.02), (0.24, 0.01, 0.00), (0.19, 0.04, 0.01), (0.20, 0.04, 0.01)]

Table 24 Dot products of fuzzy decision vectors

	φ_1	φ_2	φ_3	φ_4	φ_5
φ_1		0.176	0.197	0.161	0.188
φ_2	0.176		0.168	0.146	0.154
φ_3	0.197	0.168		0.153	0.175
φ_4	0.161	0.146	0.153		0.147
φ_5	0.188	0.154	0.175	0.147	

Table 25 β in radians for decision matrix

	β_{φ_1}	β_{φ_2}	β_{φ_3}	β_{φ_4}	β_{φ_5}
β_{φ_1}		0.938	0.996	0.938	0.985
β_{φ_2}	0.938		0.961	0.963	0.917
β_{φ_3}	0.996	0.961		0.954	0.983
β_{φ_4}	0.938	0.963	0.954		0.954
β_{φ_5}	0.985	0.917	0.983	0.954	

4.4 Ranking the decentralized energy storage investment alternatives using MF-MOPSO

Using Eq. (14), the average of the values in Table 13 is calculated and the form in Eq. (15) is constructed. The averaged $\widetilde{Q}$ for the decision matrix is given in Table 22.

Then, the values are multiplied by weights, and the rows of the weighted decision matrix are defined as fuzzy vectors. Since the number of columns is four, the t value is 4. In this case, the fuzzy vectors expressed by Eq. (16) are displayed in Table 23.

Since each row of the decision matrix represents a fuzzy vector, five fuzzy vectors are created. The dimension of the fuzzy vectors is four. Then, the dot product of these fuzzy vectors is obtained pairwise by Eq. (17). The result of dot products of MF decision vectors is summarized in Table 24.

Equation (18) is used to calculate the angle. Accordingly, the angle in radians for the elements are displayed in Table 25.

After the angles are obtained, the normalization of the angles is applied. For performing, Eq. (19) is used, while the normalized angle decision values according to different molecular geometry shapes are presented in Table 26.

In the next step, Eq. (20) used for the values of $rv\left(\beta_{\varphi_i.\varphi_j}\right)$. After that, the final values are constructed with the $rv\left(\beta_{\varphi_i.\varphi_j}\right)$. For this, Eqs. (21) and (22) are used. The final decision matrix for linear shape is illustrated in Table 27.

After constructing the final decision matrix, Eqs. (26–31) are performed for computing the positions for each particle. Details for fourth iterations are summarized in Table 28.

As can be seen in Table 28, the differs of global best positions are less than 0.001 at the fourth iteration. Therefore, the positions in this iteration are considered as the final results and the averaged positions are calculated using Eq. (32). The average values are presented in Fig. 3.

In this case, the most suitable decentralized energy storage investment alternative is hydrogen-based energy storage. Due to the advantage of MFN, the results of different molecular geometry shapes can be compared. Accordingly, the results of the strategies according to various shapes is shown in Table 29.

The consistency of the ranking results of the alternatives can be tested with different learning rates. The validity can be tested by comparing the results of the strategies according to various shapes. According to all these cases, the results are valid and consistent because the ranks of the alternatives are similar. One of the biggest advantages of hydrogen storage systems is their high storage capacity. Hydrogen can store large amounts of energy for long periods of time. This provides significant financial advantages to projects. Hydrogen-based storage systems can be integrated with renewable energy projects more successfully. Renewable energy sources can produce intermittently by nature. This deficiency can be minimized by integrating these projects with hydrogen. With the help of this issue, energy supply security can be ensured. Hydrogen-based energy storage systems offer more environmentally friendly solutions compared to fossil fuel-based applications. By implementing this, sustainable development goals can be achieved much more easily.

4.5 Sensitivity analysis

Based on Shape_1, ten different cases are constructed by changing the criterion weights. In the construction of the cases, the weights are generated by simulation without changing the priority order of the criteria. The analyses are repeated for ten different cases. The results are presented in Fig. 4.

Table 26 Normalized β values according to different molecular geometry shapes

Linear	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})	Normalize(β_{φ_5})
Normalize(β_{φ_1})	0.000	0.112	0.027	0.112	0.056
Normalize(β_{φ_2})	0.112	0.000	0.089	0.087	0.131
Normalize(β_{φ_3})	0.027	0.089	0.000	0.097	0.058
Normalize(β_{φ_4})	0.112	0.087	0.097	0.000	0.097
Normalize(β_{φ_5})	0.056	0.131	0.058	0.097	0.000
Trigonal Planar	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})	Normalize(β_{φ_5})
Normalize(β_{φ_1})	0.000	0.168	0.040	0.169	0.083
Normalize(β_{φ_2})	0.168	0.000	0.134	0.131	0.196
Normalize(β_{φ_3})	0.040	0.134	0.000	0.145	0.087
Normalize(β_{φ_4})	0.169	0.131	0.145	0.000	0.145
Normalize(β_{φ_5})	0.083	0.196	0.087	0.145	0.000
Tetrahedral	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})	Normalize(β_{φ_5})
Normalize(β_{φ_1})	0.000	0.185	0.044	0.185	0.092
Normalize(β_{φ_2})	0.185	0.000	0.147	0.143	0.215
Normalize (β_{φ_3})	0.044	0.147	0.000	0.159	0.096
Normalize(β_{φ_4})	0.185	0.143	0.159	0.000	0.159
Normalize(β_{φ_5})	0.092	0.215	0.096	0.159	0.000
Trigonal bipyramidal	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})	Normalize(β_{φ_5})
Normalize(β_{φ_1})	0.000	0.193	0.046	0.193	0.096
Normalize(β_{φ_2})	0.193	0.000	0.154	0.150	0.224
Normalize(β_{φ_3})	0.046	0.154	0.000	0.166	0.100
Normalize(β_{φ_4})	0.193	0.150	0.166	0.000	0.166
Normalize(β_{φ_5})	0.096	0.224	0.100	0.166	0.000

Table 26 (continued)

Octahedral	Normalize(β_{φ_1})	Normalize(β_{φ_2})	Normalize(β_{φ_3})	Normalize(β_{φ_4})	Normalize(β_{φ_5})
Normalize(β_{φ_1})	0.000	0.225	0.054	0.225	0.111
Normalize(β_{φ_2})	0.225	0.000	0.179	0.174	0.261
Normalize(β_{φ_3})	0.054	0.179	0.000	0.193	0.116
Normalize(β_{φ_4})	0.225	0.174	0.193	0.000	0.193
Normalize(β_{φ_5})	0.111	0.261	0.116	0.193	0.000

Table 27 The values of η

	ABT	HES	REB	DBS	FES
ABT		0.063	0.264	0.063	0.127
HES	0.063		0.079	0.081	0.054
REB	0.264	0.079		0.073	0.122
DBS	0.063	0.081	0.073		0.073
FES	0.127	0.054	0.122	0.073	

According to Fig. 4, the ranking of the alternatives is the same in ten different simulation cases, which shows the validity of the results.

5 Discussion

Customer expectations and demand are among the important criteria in improving the performance of decentralized energy storage investments. While customer expectations demand is effective in the successful development of an ecosystem, customer expectations must be understood correctly (Mainardes et al. 2023). This also helps to increase customer satisfaction (Ai et al. 2023). Siwiec and Pacana (Siwiec and Pacana 2021) proposed a photovoltaic panel selection model considering customer expectations. The proposed model involves obtaining customer expectations and then processing these criteria into technical criteria while simultaneously considering their weighting. The use of the model can help customers define their preferences, thus contributing to increased customer satisfaction with photovoltaic panels. On the other hand, Belay et al. (Belay et al. 2021) presented a new two-way approach to assess the gap between customer needs and technology developers' perceptions regarding the value propositions of innovations involving storage areas. Because understanding and interacting with customer needs is vital for the successful launch of newly developed technologies and innovations. Current models do not sufficiently take into consideration customer expectations. In most studies, the performance of energy storage investments is analyzed by examining technical and economic criteria. However, customer expectations are not directly considered as an input. This situation includes the risk of not fully reflecting user demands. This study offers a unique approach to improving the performance of energy storage investments with a new model that considers customer

Table 28 Velocity and Positions

	ABT (($V_1(1)$)	HES (($V_2(1)$)	REB (($V_3(1)$)	DBS (($V_4(1)$)	FES (($V_5(1)$)	ABT (($PR_1(1)$)	HES (($PR_2(1)$)	REB (($PR_3(1)$)	DBS (($PR_4(1)$)	FES (($PR_5(1)$)	(($P_{gb}(1)$)	(($P_{gb}(t)$) − (($P_{gb}(t-1)$))
ABT		0.00	0.00	0.00	0.02	0.00	0.06	0.26	0.06	0.13	0.26	–
HES	− 0.01		0.01	0.00	0.01	0.06	0.00	0.08	0.08	0.05	0.08	–
REB	− 0.01	− 0.03		0.00	0.02	0.26	0.08	0.00	0.07	0.12	0.26	–
DBS	− 0.01	0.00	0.01		0.00	0.06	0.08	0.07	0.00	0.07	0.08	–
FES	0.00	0.00	0.00	− 0.01		0.13	0.05	0.12	0.07	0.00	0.13	–
	ABT (($V_1(2)$)	HES (($V_2(2)$)	REB (($V_3(2)$)	DBS (($V_4(2)$)	FES (($V_5(2)$)	ABT (($PR_1(2)$)	HES (($PR_2(2)$)	REB (($PR_3(2)$)	DBS (($PR_4(2)$)	FES (($PR_5(2)$)	(($P_{gb}(2)$)	(($P_{gb}(t)$) − (($P_{gb}(t-1)$))
ABT		0.14	− 0.01	0.15	0.10	0.00	0.35	0.28	0.35	0.32	0.28	0.01
HES	0.01		0.00	0.00	0.02	0.09	0.00	0.08	0.08	0.09	0.08	0.00
REB	0.00	0.13		0.14	0.10	0.27	0.34	0.00	0.34	0.32	0.26	0.00
DBS	0.01	0.00	0.00		0.01	0.09	0.08	0.08	0.00	0.08	0.08	0.00
FES	− 0.01	0.05	0.00	0.04		0.13	0.16	0.13	0.15	0.00	0.13	0.01
	ABT (($V_1(3)$)	HES (($V_2(3)$)	REB (($V_3(3)$)	DBS (($V_4(3)$)	FES (($V_5(3)$)	ABT (($PR_1(3)$)	HES (($PR_2(3)$)	REB (($PR_3(3)$)	DBS (($PR_4(3)$)	FES (($PR_5(3)$)	(($P_{gb}(3)$)	(($P_{gb}(t)$) − (($P_{gb}(t-1)$))
ABT		− 0.09	0.09	− 0.10	− 0.03	0.00	0.35	0.30	0.35	0.32	0.35	0.08
HES	0.00		0.01	0.01	− 0.01	0.09	0.00	0.08	0.08	0.09	0.09	0.01
REB	0.10	− 0.09		− 0.09	− 0.04	0.31	0.34	0.00	0.34	0.32	0.34	0.08
DBS	− 0.01	0.01	0.01		0.00	0.09	0.09	0.08	0.00	0.08	0.09	0.01
FES	0.03	− 0.04	0.04	− 0.01		0.14	0.16	0.14	0.15	0.00	0.16	0.03
	ABT (($V_1(4)$)	HES (($V_2(4)$)	REB (($V_3(4)$)	DBS (($V_4(4)$)	FES (($V_5(4)$)	ABT (($PR_1(4)$)	HES (($PR_2(4)$)	REB (($PR_3(4)$)	DBS (($PR_4(4)$)	FES (($PR_5(4)$)	(($P_{gb}(4)$)	(($P_{gb}(t)$) − (($P_{gb}(t-1)$))
ABT		− 0.33	0.07	− 0.35	− 0.18	0.00	0.35	0.37	0.35	0.32	0.35	0.00
HES	− 0.02		0.01	0.01	− 0.05	0.09	0.00	0.09	0.09	0.09	0.09	0.00
REB	0.05	− 0.31		− 0.32	− 0.20	0.36	0.34	0.00	0.34	0.32	0.34	0.00
DBS	− 0.03	0.01	0.00		0.00	0.09	0.09	0.09	0.00	0.08	0.09	0.00

Table 28 (continued)

	ABT $((V_1(4))$	HES $((V_2(4))$	REB $((V_3(4))$	DBS $((V_4(4))$	FES $((V_5(4))$	ABT $((PR_1(4))$	HES $((PR_2(4))$	REB $((PR_3(4))$	DBS $((PR_4(4))$	FES $((PR_5(4))$	$((P_{\mathrm{gb}}(4))$	$((P_{\mathrm{gb}}(\mathrm{t})) - ((P_{\mathrm{gb}}(\mathrm{t} - 1))$
FES	0.03	− 0.13	0.03	− 0.07		0.16	0.16	0.16	0.15	0.00	0.16	0.00

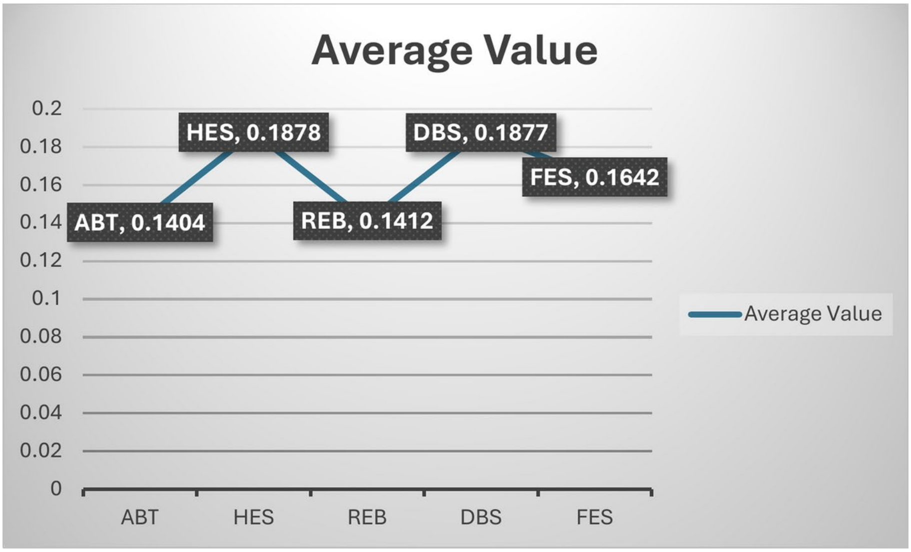

Fig. 3 The average value

Table 29 The comparative ranking results of the alternatives

Learning rate: .1	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
ABT	5	5	5	5	5
HES	1	1	1	1	1
REB	4	4	4	4	4
DBS	2	2	2	2	2
FES	3	3	3	3	3
Learning rate: .5	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
ABT	5	5	5	5	5
HES	1	1	1	1	1
REB	4	4	4	4	4
DBS	2	2	2	2	2
FES	3	3	3	3	3
Learning rate: 1	Shape_1	Shape_2	Shape_3	Shape_4	Shape_5
ABT	5	5	5	5	5
HES	1	1	1	1	1
REB	4	4	4	4	4
DBS	2	2	2	2	2
FES	3	3	3	3	3

expectations. It offers customized solutions for the importance of feedback mechanisms and comprehensive demand analyses.

Finance has been identified as another important criterion in improving the performance of decentralized energy storage investments. In other words, the development of innovative models is very important for ensuring financial sustainability. While this situation requires additional capital for the development of new technologies, it is seen that programs are being developed and implemented in some countries to encourage the financial sector to

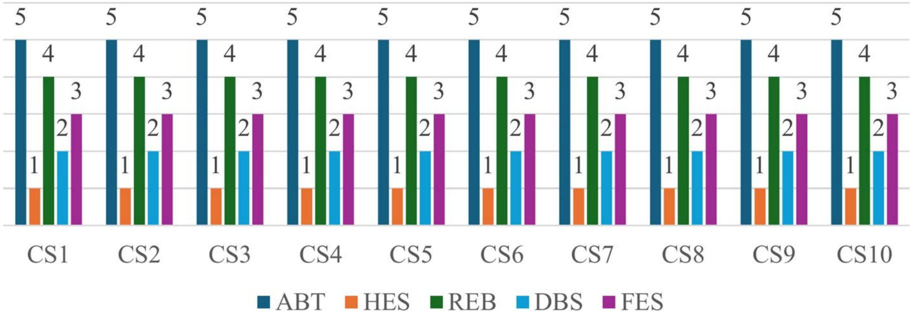

Fig. 4 The output of sensitivity analysis

invest in renewable energy projects (Tsao et al. 2021). In addition, subsidy policies for improving financial performance for energy storage also have a significant impact, while they are adjusted according to technological progress, changes in market competition and other factors (Sun et al. 2023). Berrada (Berrada 2022) evaluated the financial performance of a new energy storage system. Because energy storage systems examined from a financial and economic perspective; can be considered among the applicable technologies for storing large-scale energy capacities since they provide sufficient returns for project investors, have a high ability to meet debt payments from cash flows and provide sufficient financial performance. Rotella et al. (Rotella Junior et al. 2021) presented a literature review on the economic analysis of battery energy storage systems. In doing so, they reveal the increasing interest of batteries as energy storage systems to improve the technoeconomic viability of renewable energy systems. In this way, it will be able to provide a comprehensive overview of the main methodological possibilities for researchers interested in the economic analysis of battery energy storage systems, highlight the need to use adequate economic indicators for investment decisions and identify the main research topics of the analyzed literature. A significant portion of the studies in the literature focus on current cost analyses and short-term economic evaluations. However, issues such as long-term financial sustainability are not sufficiently analyzed. This study addresses long-term financial modeling and risk management strategies. Owing to this situation, the sustainability of energy storage investments can be addressed more comprehensively. Another important issue in existing models is that they generally consider fixed incentive mechanisms. This study analyzes the impact of changing subsidy policies.

6 Conclusion

This study highlights the critical importance of decentralized energy storage investments to provide energy efficiency by proposing a novel decision-making model. The integration of information gain-based mass expert selection, q-learning algorithm, molecular fuzzy cognitive maps, and MF MOPSO is taken into consideration to identify the most critical factors and optimal investment strategies. The findings underline the significance of customer expectations and financial considerations for improving decentralized energy storage projects. Moreover, hydrogen-based energy storage and distributed battery swapping stations emerge as the most promising alternatives for these investments. The main limitation of the study is that the experts are selected from a limited geographical or sectoral perspective. This may limit the generalizability of the results. Future studies can work with expert groups with a wider geographical distribution and sectoral diversity. Owing to this situation, the validity of the model can be increased. Another limitation is that the criteria and alternatives determined in the study reflect the current situation. On the other hand, technological developments in the energy sector are rapid. Because of this issue, these criteria may change over time. In future studies, the model can be designed to make dynamic updates. Moreover, the results of the study are generally considered in a specific regional context. Nevertheless, regional and global differences in the energy sector may play an important role. To overcome this limitation, the model can be applied in different countries or regions in the following studies. With the help of this condition, more comprehensive results can be obtained for international energy projects. Additionally, these findings of this study mainly rely on the expert opinions. This situation creates a subjectivity problem for this study. Thus, as a future research direction, an econometric analysis can also be conducted for this subject.

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Data availability The data used to support the findings of this study are included within the article.

Declarations

Conflict of interest The authors declare no conflicts of interest.

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