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Information-gain based project prioritization and q-learning molecular fuzzy ranking for energy positive building investments

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ABSTRACT

Energy-positive buildings have gained significant attention as a sustainable solution to the growing global energy crisis. However, the efficient allocation of limited resources remains major challenges for optimizing these investments. There is a need for a new priority analysis for these factors. This article aims to determine the appropriate investment strategies regarding energy positive building projects via a novel model. The relevant project factors are detected using the information gain-based attribute selection in the first stage. The balanced evaluation matrices are created by q-learning in the following section. The weights of performance indicators are computed by molecular fuzzy cognitive maps. Moreover, project alternatives for energy positive building investments are examined via molecular fuzzy multi-objective particle swarm optimization. The main contribution of this study to the literature is that prior investment strategies for the improvements of the energy positive building projects can be identified with the help of a novel decision-making model. The main superiority of the proposed methodology is calculation of the importance weights of the experts. The results illustrate that the information gain method reduces the initial eight project alternatives to five, with the highest information gain values (0.750 for energy production potential and 1.000 for the use of high-performance materials) highlighting the most influential factors. The q-learning algorithm balances expert evaluations, achieving convergence with a tolerance of 0.02, ensuring stability in decision matrices. The MF cognitive maps assign weights to criteria, with the use of high-performance materials (weight: 0.256) and technological infrastructure (weight: 0.253) emerging as the most critical. The MF-MOPSO ranking results show consistent performance across five molecular geometry shapes, with the vertical urban farming tower (average score: 0.1562) and net-positive educational campus (average score: 0.1560) as the top alternatives. The model's superiority is further validated through comparative analysis with the ARAS method, confirming robustness against weight variations (1–2 % changes). These results provide actionable insights for policymakers and

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investors to allocate resources effectively, emphasizing high-performance materials and technological advancements as key drivers for energy-positive building investments.

1. Introduction

Energy positive buildings are constructions that meet their own energy needs. In addition, these buildings can also provide energy to the main grid by generating additional energy. These buildings have some advantages. Firstly, low energy consumption is possible in energy positive buildings. The energy efficiency of the projects can be increased. Energy positive buildings also increase the use of renewable energy. It contributes significantly to the reduction of carbon emissions. These projects also include some economic advantages. Thanks to energy production, the need to purchase energy from outside is reduced. Similarly, additional income can be obtained by selling excess energy to the grid. To increase the performance of these projects, some aspects need to be improved. Energy production potential is a critical factor for the performance of energy positive building projects. By increasing the energy production potential, it is possible to meet energy demands more successfully. Technological infrastructure is also an essential element for the performance of energy positive building projects. Improving the technological infrastructure increases the effectiveness of energy storage systems (Shirinbakhsh and Harvey, 2024). The use of high-performance materials is critical to the performance of energy-positive building projects. Environmentally resistant materials reduce maintenance costs and extend building life.

To optimize the performance of energy positive building investments, it is necessary to determine the most effective indicators. Determining these factors allows for more efficient and sustainable results to be obtained in all stages of the projects. This is especially necessary for the efficient use of resources. The resources of energy positive building investment companies are quite limited. Hence, focusing on high-impact indicators provides a more efficient process in terms of time and cost. Determining these factors is also necessary to reduce investment risks (Korab et al., 2024). Correctly determining performance indicators forms the basis for predicting and minimizing risks that may occur during the project. Furthermore, more important factors must be found to ensure goal-oriented performance management. The aim of energy positive buildings is to present a building model where energy production exceeds consumption. Critical indicators must be determined to achieve this goal. Multi-criteria decision-making analysis can be performed to perform priority analysis for performance indicators (Prades-Gil et al., 2024). These evaluations can be very helpful for the companies to identify prior areas in their investments. On the other hand, there are few studies in the literature where such analyses are performed. It is necessary for determining the right investment strategies.

The purpose of this study is to define prior investment strategies regarding the energy positive building projects. In the first stage, the relevant project factors are detected using the information gain-based attribute selection. In this process, entropy values and information gain are calculated. The second stage is related to the creation of the balanced evaluation matrices by q-learning. For this purpose, vectors and angles are determined. The third stage focuses on the criteria weighting process with the help of molecular fuzzy (MF) cognitive maps. In the last stage, project alternatives for energy positive building investments are evaluated via MF multi-objective particle swarm optimization (MOPSO). Two research questions can be created for this study as detailed below. (1) Which performance indicators of the energy positive building projects have the greatest weights? (2) Which project alternatives should be mainly considered by the investors to improve the effectiveness of energy positive building projects? The motivations for this study are based on the necessity to determine critical performance indicators to optimize the performance of energy positive building investments. The resources of companies that carry out energy positive building investments are usually limited. Therefore, it is necessary to focus on indicators with high impact. It contributes significantly to the increase in efficiency in operational processes. In addition to them, it is also of vital importance for minimizing the risks of the projects. There are many different risks in the operational processes of energy positive building investments. The correct determination of performance indicators is very important for minimizing these risks.

The main contribution of this study to the literature is that prior investment strategies for the improvements of the energy positive building projects can be identified with the help of a novel decision-making model. The main superiorities of the proposed model can be defined as follows.

(1) In the decision-making model of the study, the weight values of the experts are determined. In this process, the opinions of the expert whose weight is determined as high are taken into consideration more. It has advantages compared to other similar decision-making models. The knowledge level, experience and expertise degree of the experts are different from each other. With this method, the opinions of the experts with more knowledge and experience are prioritized. The decision-making process can be based on a more realistic basis. Experts with insufficient knowledge may have a negative effect on the decision. This negative situation is minimized by weighting the expert opinions. Expert weights can be determined dynamically by using artificial intelligence-based algorithms such as q-learning. It allows the model to be adapted more easily according to changing conditions. A significant part of the decision-making models in the literature assigns equal importance to the opinions of the experts. The most important disadvantage of these models is that experts with low knowledge levels also have an effect on the decision process. In this model, a weighting is made based on the knowledge level and expertise degree of the experts. More effective and result-oriented decision-making process can be provided.

(2) In this study, a new fuzzy set is used with the name of MF sets. In this process, fuzzy logic is integrated with the molecular geometry approach. There are many different shapes in molecular geometry. It is aimed to reduce the uncertainty in the process by integrating these different shapes into fuzzy decision-making processes. On the other hand, it is possible to create a

normalized matrix more effectively. In this study, the integration of the molecular geometry approach with fuzzy logic makes important contributions to the literature. The integration of the molecular geometry approach into fuzzy decision-making processes allows uncertainty to be managed more effectively. Traditional fuzzy set models are generally not sufficient to represent uncertainty. In molecular geometry, there are many different shapes such as linear, trigonal, tetrahedral. It provides better modeling of uncertainty, especially in complex decision-making problems. On the other hand, the molecular geometry approach allows normalized matrices to be created more effectively. In this way, the error rate in the decision-making process is reduced and more reliable results are achieved. Intuitionistic fuzzy sets use two parameters for each element, the degree of belonging and the degree of not belonging. It may be difficult to capture the uncertainty completely. MF sets offer a more dynamic and flexible structure. In this condition, it expresses more complex and variable structures more effectively. Pythagorean fuzzy sets may not produce very effective results, especially in the analysis of complex relationships. MF sets provide a more dynamic and three-dimensional uncertainty modeling in connection with molecular geometry. This application also allows the specified problem to be managed more effectively.

(3) The use of the cognitive maps technique in criterion weighting provides some advantages to the model. This method defines direct and indirect relationships between the criteria. On the other hand, feedback loops between the factors are considered with this technique. This technique has some advantages compared to its counterparts in the literature. For example, the analytic hierarchy process assumes that the criteria are independent. On the other hand, in the real world, the criteria contain dynamic elements that affect each other. Dynamic and causal relationships can be taken into consideration by using the cognitive maps technique. Moreover, the hierarchical structure is mandatory in the analytic hierarchy process technique. On the other hand, this approach may not be very suitable for large-scale environmental and technological systems. Thanks to the cognitive maps approach, the analysis can be adapted to continuous data flow and changing conditions. A more effective solution to this problem may be possible.

(4) With the multi-objective particle swarm optimization approach, the ranking of alternatives also makes the model more effective compared to others. With this technique, a swarm intelligence-based optimization is performed. This contributes to the results being more accurate and reliable. Another advantage of this technique is that it does not have to take into account local maximum data. It can optimize more than one target at the same time. With this feature, it is more suitable for the analysis of a complex issue such as the development of energy positive building projects. The technique for order preference by similarity to ideal solution (TOPSIS) technique determines a single best alternative. In contrast, the multi-objective particle swarm optimization approach can produce a set of Pareto optimal solutions. Similarly, TOPSIS assumes linear dependence. Nevertheless, multi-objective particle swarm optimization can also handle nonlinear relationships.

The content of this study is designed as follows. Literature evaluation is conducted in the second section. With the help of this issue, the main gap in the literature can be identified. To fill this gap, a novel model is proposed that is detailed in the third section. The fourth section focuses on the results of this model. In the final sections, the main conclusions and discussion of the results are taken place.

2. Literature review

One of the important criteria affecting investment in energy-positive buildings is energy production potential (Mainini et al., 2024). A building can be considered energy-positive if it produces more energy than it consumes. Therefore, it is essential to select appropriate energy sources for the building (Mohammed et al., 2023). Furthermore, the long-term profitability and economic sustainability of the project are affected by its energy production potential (Sebastian, 2024). The climatic conditions in the region to be invested in are decisive in terms of energy production capacity (Aljashaami et al., 2024). Barrut et al. examined the decision-making process within the framework of key performance indicators for positive energy-building design. In this process, it is argued that energy demand should be reduced, and the importance of energy production potential is emphasized. Suarez-Ramon et al. (2024) conducted a study to upgrade a building to a zero-energy building. The results of the study, which emphasize the need for efficiency in energy consumption, show the importance of production potential for investment.

Technological infrastructure is an important factor affecting energy-positive building investments (Moudgil et al., 2023). Technological infrastructure plays a crucial role in integrating energy production systems into buildings (Elnour et al., 2024). It also enables the availability of smart systems and software in the building. In addition, monitoring and managing energy production and consumption can be possible with technological tools (Sözer et al., 2023). The quality and modern structure of the technological infrastructure affect energy costs in the long run. Therefore, it can also directly affect the payback period of the investment (Wang et al., 2024). Li et al. (2023) assessed policies and technologies for low-carbon buildings and communities. It is understood that minimum carbon emission, energy saving, and energy-positive buildings are directly related to technology and related infrastructure. Gade and Selamn (2023) carried out a case study on the implementation of sustainable development goals in construction projects. The importance of infrastructure for the implementation of sustainable development goals and the success of the energy-positive process is emphasized.

The use of high-performance materials is another important factor influencing investments in energy-positive buildings (de Castro et al., 2024). Although the initial costs of high-performance materials are high, they can shorten the return on investment in the long run (Xu et al., 2024). Moreover, energy-positive buildings constructed with such materials are more likely to be in higher demand. In addition, they contribute positively to achieving energy independence as they significantly reduce energy consumption. Considering the changing legal processes, it also meets future regulations (Mohamed Abdelhaleem et al., 2024). Annaba et al. (2024) aimed to ensure building efficiency in the Moroccan climate. The necessity of using high-performance materials to achieve this goal is emphasized. Miao et al. (2024) conducted a study within the scope of library buildings to provide sustainable architecture considering future climate conditions. It is stated that the use of high-performance materials such as windows serves this purpose.

The capacity of smart systems is an important factor influencing investment decisions. Smart systems play a vital role in optimizing energy production and consumption processes. Therefore, they contribute to energy efficiency and cost reduction (Abdallah, 2023). Moreover, meeting changing energy demands is associated with the capacity and flexibility of smart systems. In addition, smart systems have an effective place in detecting potential problems and taking measures with a proactive approach. The use of smart systems in buildings also provides a significant competitive advantage (Bayasgalan et al., 2024). Wang et al. (2023) aimed to make intelligent design and environmental assessment of green buildings using biomass and solar energy. It is concluded that integrating smart systems into buildings reduces the cost and leads to lower carbon emissions. Mirjalili et al. (2023) conducted a study to ensure the sustainability of office buildings. It is stated that it is advantageous to utilize solar panels and smart charging to provide energy efficiency.

Energy-positive buildings offer an important solution for a sustainable future. In addition, their many environmental and economic benefits increase the importance of investments in energy-positive buildings. However, several factors affect investments in energy-positive buildings. The literature review shows that energy production potential is one of the main factors for buildings to become energy positive. Apart from this, technological infrastructure has an important place in its integration with energy systems and its impact on the return on investment. The use of high-performance materials influences the investment decision as they contribute to energy efficiency. In addition, smart system capacities have a significant impact on the flexibility they provide to meet changing demands. Improving all these criteria positively affects investment decisions. However, it is not possible to intervene in all criteria at the same time. Therefore, weighting the criteria affecting energy-positive building investments in order of importance fills an important gap in the literature. Accordingly, this study aims to identify the most important criteria affecting energy-positive building investments and to develop a prioritized strategy. Consequently, this study is intended to shed light on both theoretical knowledge and

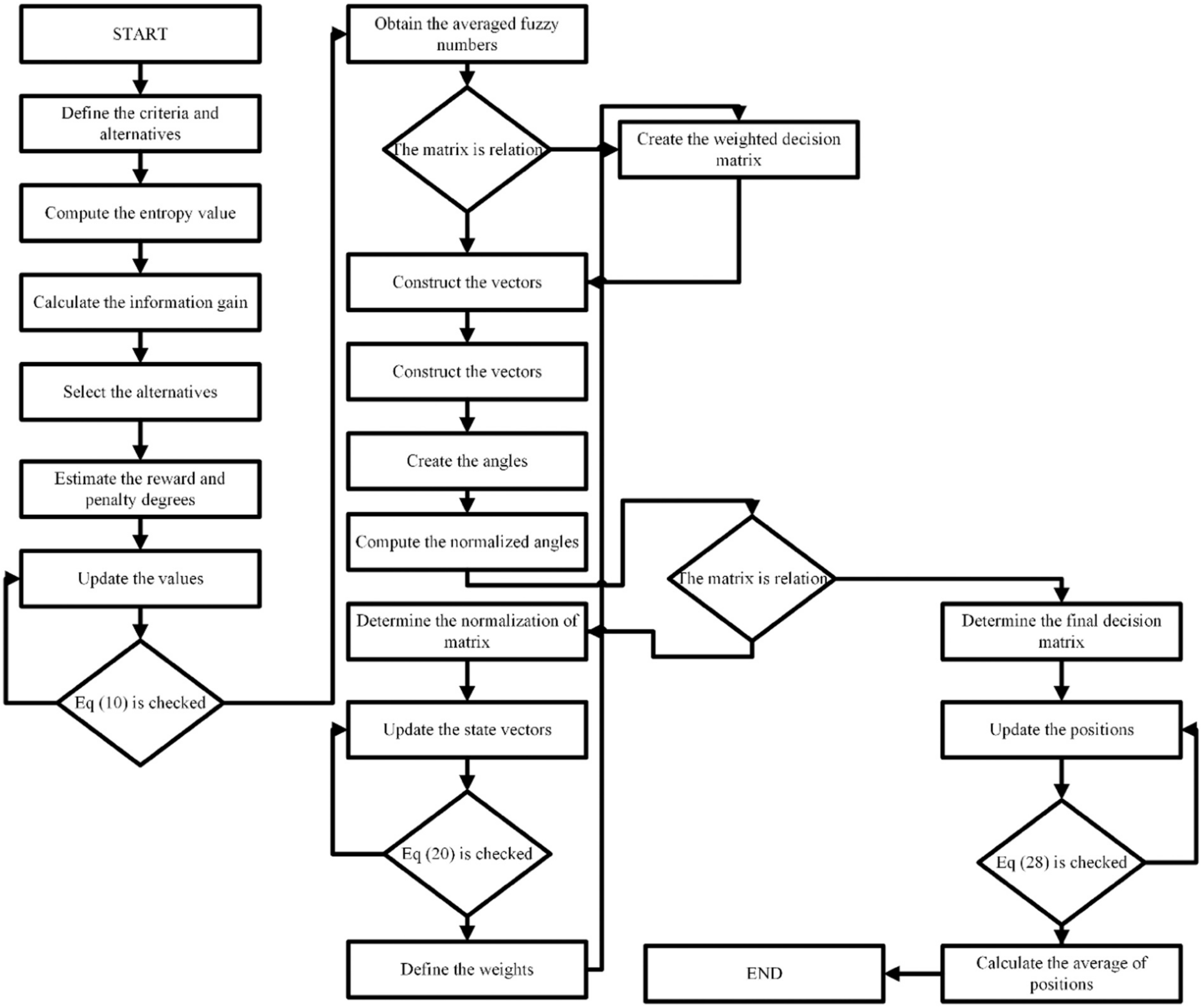

Fig. 1. The step-by-step representation of the proposed methodology.

practical applications.

3. Methodology

In this section, the models included in the proposed methodology for ranking project alternatives of energy positive building are introduced. Since the number of project alternatives for energy positive buildings is high, the information gain-based project prioritization method is preferred to reduce the number of alternatives. After determining the number of alternatives, criteria are selected for the project evaluation of energy positive buildings. Then, expert evaluations are collected, and Q-learning algorithm is integrated into the model to create balanced evaluation matrices. After creating evaluation matrices as data, criterion weighting and then ranking of project alternatives are performed with MF cognitive maps and MOPSO methods, respectively. In this process, MF numbers, which are a set of fuzzy logic, are used. In this way, both uncertainty is analyzed and comparison of results according to different shapes is possible. The step-by-step representation of the proposed methodology is visualized in Fig. 1.

3.1. MF sets

Fuzzy logic is a set theory developed for the analysis of uncertainty. This theory, which is influenced by different disciplines and developed every year, includes different set definitions such as quantum and Pythagoras. MF sets, developed using molecular geometry shapes, are based on the theory called “Valence Shell Electron Pair Repulsion”. According to this set definition, an element (a) with membership ($\mathfrak{m}$), non-membership ($\mathfrak{v}$) and hesitancy ($\jmath$) components must satisfy the condition in Eq. (1) (Gentili, 2024).

$$\mathfrak{m}_A(a) + \mathfrak{v}_A(a) + \jmath_A(a) = 1 \tag{1}$$

A is any MF set in a universe of discourse. Accordingly, the membership function of an element is defined as the normalization of angle according to the molecular geometries by Eq. (2).

$$\mathfrak{m}_A(a) = f(\theta_a) = 1 - \frac{\theta_a}{\theta_{\max}} \tag{2}$$

Similarly, Eqs. (3) and (4) express the non-membership and hesitancy functions of an element, respectively.

$$\mathfrak{v}_A(a) = \frac{\theta_a}{\theta_{\max}} \tag{3}$$

$$\jmath_A(a) = 1 - \left(\left(1 - \frac{\theta_a}{\theta_{\max}}\right) + \frac{\theta_a}{\theta_{\max}} \right) \tag{4}$$

3.2. Information gain-based project prioritization

Choosing the most appropriate alternative for decision making is vital in areas that require high expertise. It becomes difficult to obtain expert evaluations and see the differences between alternatives to evaluate a large number of alternatives. For these reasons, an objective alternative number reduction method is needed. This method analyzes the criteria of the alternatives as input attributes and initial expert evaluations on certain criteria as outputs based on information gain and is used to select the most appropriate alternatives. The basic stages of the method can be expressed as follows (Zhang et al., 2024).

The first stage describes the characteristics of the alternatives and the qualitative expert ratings in linguistic terms, thus representing the information about the alternatives and the evaluation of each expert on the decision criteria and allowing quantitative analysis on the qualitative assessments. Based on initial expert evaluations, expert choices for each outcome are calculated using the entropy measure for each outcome to quantify the uncertainty or distortion in the ratings of each criterion across alternatives. This measure provides information on how well different alternative attributes explain the variability. The entropy is computed with Eq. (5).

$$E(O) = -\sum_{i=1}^{n} p_i \log_2(p_i) \tag{5}$$

Where O is the criterion in the output set, n is the number of the unique ratings, p_i is the probability of each rating in the alternative dataset. After that, the information gain values are estimated for each input attribute using Eq. (6).

$$G(A, O) = E(O) - \sum_{v \in A} \frac{|O_v|}{|O|} E(O_v) \tag{6}$$

This value expresses how much entropy is reduced when splitting based on each alternative input. Then, the weighted entropy for each output is determined using the weights of the alternative inputs in the total alternatives. In this way, the overall entropy values are obtained for the input of the alternative in the output of the selected alternative. Similarly, this calculation is applied to the other alternative inputs and outputs to calculate the information gain for all pairings. Finally, the most suitable alternative input with the highest information gain value for each criterion is selected. Thus, a set of rules defining the most effective alternative characteristics is created.

3.3. Q-learning algorithm

Experience knowledge is one of the higher important issues in the evaluations of experts. Experience knowledge can be expressed as a combination of many factors such as experience period, education. For this reason, this algorithm is used to balance the evaluation matrices of other experts according to the evaluation matrix of the expert with the highest experience. The basic stages of the method can be expressed below (Guo et al., 2024).

First, evaluations are obtained from experts, and the evaluations are transformed into MFN. Thus, the fuzzy evaluation matrices Q are obtained. Then, the lead expert is selected. Usually, the years of experience are examined in literature and the expert with the highest years of experience is selected as the lead expert. Accordingly, the normalized values of the experience periods of the experts are used as reward and penalty factors. After the lead expert is selected, reward and penalty degrees are obtained among the experts with the help of fuzzy evaluation matrices. Eq. (7) defines the computation of the reward degree, while Eq. (8) defines the calculation of the penalty degree.

$$DR_{s,a} = fcr_r \times \left(Q_{s,a}{}^{lead} - Q_{s,a}{}^{others}\right) \tag{7}$$

$$DP_{s,a} = fcr_p \times \left(Q_{s,a}{}^{others} - Q_{s,a}{}^{lead}\right) \tag{8}$$

Where fcr_r and fcr_p are factors of reward and penalty. Using the $DR_{s,a}$ and $DP_{s,a}$ matrices, Eq. 9 is about updating of fuzzy evaluation matrices.

$$Q_{s,a}^{\text{updated}} = Q_{s,a}{}^{lead} + fcr_l \times \left(DR_{s,a} - DP_{s,a}\right) \tag{9}$$

Where fcr_l means learning rate. This updating process continues until optimal fuzzy evaluation matrices are created. Eq. (10) defines the convergence check for creating optimal fuzzy decision-making matrices.

$$\max_{s,a} \{| Q_{s,a}^{updated} - Q_{s,a} |\} < .02 \tag{10}$$

The updated values in the iteration where the condition is met are defined as elements of stable fuzzy evaluation matrices.

3.4. MF cognitive maps

This method, which is used in solving nonlinear problems, analyzes the interaction of the criteria. In this way, the method models the complex system of relationship criteria in the matrices. The basic stages of the method can be expressed as follows (Ouyang et al., 2024).

First, experts determine the degree of dependency between the criteria. An evaluation matrix is constructed for each expert with linguistic values. These linguistic term matrices are then transformed into MFNs. Then, the average of each expert's evaluation is computed, and the MF direct relation matrix is obtained. Eq. (11) shows the averaging operator for MFNs, while Eq. (12) forms the MF direct relation matrix.

$$r = \left(\bigcup_{i=1}^{k} r_i\right) = \left\{\left(a, \frac{1}{k}\sum_{i=1}^{k} \mathfrak{m}_{r_i}(a), \frac{1}{k}\sum_{i=1}^{k} \mathfrak{v}_{r_i}(a), \frac{1}{k}\sum_{i=1}^{k} \mathfrak{s}_{r_i}(a)\right) \mid a \in A\right\} \tag{11}$$

$$RM = \begin{bmatrix} 0 & r_{12} & \cdots & \cdots & r_{1n} \\ r_{21} & 0 & \cdots & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{12}$$

Afterwards, each row of the RM is defined as a vector, so that the angle between them can be used to utilize molecular geometry. The point to be noted here is that since RM does not have diagonal values, the magnitude of the vectors for the RM is n-1. In this way, n vectors are constructed. Eq. (13) defines the construction of the vector from i-row.

$$u_i = \left[(\mathfrak{m}_{i1}, \mathfrak{v}_{i1}, \mathfrak{s}_{i1}), (\mathfrak{m}_{i2}, \mathfrak{v}_{i2}, \mathfrak{s}_{i2}), \ldots, (\mathfrak{m}_{il}, \mathfrak{v}_{il}, \mathfrak{s}_{il})\right] \tag{13}$$

Where l is the magnitude of the vector. Then, the angles among the vectors are obtained. Eq. (14) defines the angle.

$$\theta_{u_i,u_j} = \cos^{-1}\left(\frac{\sum_{t=1}^{l}\left(\mathfrak{m}_{i,t}\cdot\mathfrak{m}_{j,t} + \mathfrak{v}_{i,t}\cdot\mathfrak{v}_{j,t} + \mathfrak{s}_{i,t}\cdot\mathfrak{s}_{j,t}\right)}{\left(\sum_{t=1}^{l}\left(\mathfrak{m}_{i,t}^2 + \mathfrak{v}_{i,t}^2 + \mathfrak{s}_{i,t}^2\right)\right)\cdot\left(\sum_{t=1}^{l}\left(\mathfrak{m}_{j,t}^2 + \mathfrak{v}_{j,t}^2 + \mathfrak{s}_{j,t}^2\right)\right)}\right) \tag{14}$$

In the other stage, the normalization of angle is obtained according to various molecular geometry shapes. Eq. (15) includes the calculation of the normalized angle.

$$norm\left(\theta_{u_i,u_j}\right) = \begin{cases} \dfrac{\theta_{u_i,u_j}}{\theta_{\max}} \\ \dfrac{\theta_{u_i,u_j}}{\pi} \\ \dfrac{\theta_{u_i,u_j}}{\frac{2\pi}{3}} \\ \dfrac{\theta_{u_i,u_j}}{\frac{\pi}{2}} \\ \dfrac{\theta_{u_i,u_j}}{\frac{2\pi}{5}} \\ \dfrac{\theta_{u_i,u_j}}{\frac{\pi}{3}} \end{cases} \tag{15}$$

The selection of this piecewise normalization function is according to the general, linear, trigonal planar, tetrahedral, trigonal bipyramidal and octahedral shapes, respectively. Normalization of the relation matrix is performed with the reciprocals of the normalized angles. Eq. (16) shows the obtaining of the reciprocals of the normalized angles, while Eq. (17) forms the normalized relation matrix.

$$rp\left(\theta_{u_i,u_j}\right) = \frac{1}{norm\left(\theta_{u_i,u_j}\right)} \tag{16}$$

$$N = \begin{bmatrix} 0 & \dfrac{recip\left(\theta_{u_2,u_1}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} & \cdots & \cdots & \dfrac{recip\left(\theta_{u_1,u_n}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} \\ \dfrac{recip\left(\theta_{u_1,u_2}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} & 0 & \cdots & \cdots & \dfrac{recip\left(\theta_{u_2,u_n}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \dfrac{recip\left(\theta_{u_n,u_1}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} & \dfrac{recip\left(\theta_{u_n,u_2}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)} & \cdots & \cdots & 0 \end{bmatrix} \tag{17}$$

Using this matrix, the elements of the state vector are calculated. Eq. (18) is computing the elements.

$$A(t) = [a_1(t), a_2(t), \ldots, a_n(t)] \tag{18}$$

The initial state vector is equal to 1 and symbolized as A(0). Next, Eq. (19) is updating the state vector iteratively.

$$A(t+1) = f(A(t) \times N) \tag{19}$$

Where the function f is sigmoid function. Eq. (20) expresses the convergence condition for iterations.

$$f(A(s+1)) = f(A(s)) \tag{20}$$

When the condition is met, the values in the last iteration are defined as stabilized state vectors and the weight values of the criteria are calculated. Eq. (21) shows the calculation of the criteria with stabilized state vectors.

$$W_j = \frac{fA(s)_j}{\sum_{j=1}^{n} fA(s)_j} \tag{21}$$

3.5. MF-MOPSO

This method, which integrates MF numbers with Multi-Objective Particle Swarm Optimization, is used to rank the alternatives. It establishes Pareto optimal solutions in complex multi-objective decision-making problems and provides balanced results in these solutions. Thus, more realistic and accurate rankings are obtained. The basic stages of the method can be introduced as follows (Shen et al., 2024; Dinçer et al., 2024a,b).

First, expert evaluations are collected for decision matrix. An evaluation matrix is constructed for each expert with linguistic values. These linguistic term matrices are then transformed into MFNs. Then, the average of each expert's evaluation is computed, and the MF decision matrix is obtained. Eq. (11) shows the averaging operator for MFNs, while Eq. (22) forms the decision matrix.

$$X = \left[X_{ij}\right]_{m\times n} \tag{22}$$

The weights of the criteria are multiplied by the X matrix and the weighted decision matrix is calculated. Afterwards, each row of the weighted decision matrix is defined as a vector, so that the angle between them can be used to utilize molecular geometry. The point to be noted here is that the magnitude of the vectors for this matrix is n. In this way, m vectors are constructed. Eq. (13) defines the construction of the vector from i-row. Then, the angles among the vectors are obtained. Eq. (14) defines the angle. In the other stage, the normalization of angle is obtained regarding to various molecular geometry shapes. Eq. (15) includes the calculation of the normalized angle. The selection of this piecewise normalization function is according to the general, linear, trigonal planar, tetrahedral, trigonal bipyramidal and octahedral shapes, respectively. Normalization of the relation matrix is performed with the reciprocals of the normalized angles. Eq. (16) shows the obtaining of the reciprocals of the normalized angles, while Eq. (23) forms the final decision matrix.

$$F = \left[\frac{recip\left(\theta_{u_i,u_j}\right)}{\sum_{j=1}^{n} recip\left(\theta_{u_i,u_j}\right)}\right] \tag{23}$$

Using this matrix, the velocity, positions are estimated. Eq. (24) shows a vector for the particle presentation to solutions.

$$X_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\} \tag{24}$$

Afterwards, Eq. (25) is updating the velocity of each particle.

$$V_{ij}(t+1) = 0.5V_{ij}(t) + 1.5r_1\left(P_{ij}(t) - X_{ij}(t)\right) + 1.5r_2\left(P_{gb_j}(t) - X_{ij}(t)\right) \tag{25}$$

Where the random variables are r_1 and r_2. $r_1, r_2 \in [0, 1]$. Moreover, Eq. (26) defines the initial velocity.

$$V_{ij}(1) = 0.1\left(P_{\max_i} - P_{\min_i}\right)y \tag{26}$$

Where $y \in [-1, 1]$. Later, Eq. (27) is updating the positions.

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{27}$$

The iteration continues until the condition in Eq. (28) is met.

$$\left|P_{gb_j}(t+1) - P_{gb_j}(t)\right| < .001 \tag{28}$$

The alternatives are ranked according to the average of the positions in the iteration where the condition is met.

4. Analysis

Energy positive building study findings are as follows.

4.1. Constructing the MF numbers

MF number forms of linguistic expressions are constructed in accordance with Eq. (1). Accordingly, MF numbers for the five-point

Table 1
The linguistic expressions and MFN.

Linguistic Expression	MFN
Negligible	(.20,.70,.10)
Low	(.40,.50,.10)
Moderate	(.60,.30,.10)
Significant	(.80,.15,.05)
High	(.95,.05,.00)

scale are given in Table 1.

Expert assessments are carried out according to the scale in Table 1. Thus, Eqs. (2)-(4) is obtained. Table 1 indicates that there are five different scales. Additionally, for each scale, a different MF set is proposed.

4.2. Detecting the relevant project factors using the information gain-based attribute selection

The criteria used in the project evaluation of energy positive buildings are energy production potential (EPP), technological infrastructure (TI), use of high-performance materials (UHM), capacity of smart systems (CSS). Similarly, eight alternatives are determined. However, since the evaluation of eight alternatives would be challenging, a reduction decision is made with this method. The expert with the highest experience is the lead expert and his views are analyzed. In other words, projects with their specifications and initial output feedback are defined.

The weights of the experts are computed by considering the expertise in the construction and energy industry. Expert 1 has more than 20 years' experience in construction and sustainable building projects internationally. The other experts have equally 15 years' experience in energy investments. So, the first expert is defined as lead expert in the team and the initial assessments of lead expert are considered for information-gain based project selection. Accordingly, the first expert is assigned with the weight of 0.500, the equal weights of 0.250 are given for the other experts. Based on these expert weights, the first expert is selected as the most experienced decision-maker with a weight of 0.500 in the expert team. Table 2 shows project specifications and the initial criteria review by the lead expert.

F1, F2, F3 and F4 are annual energy surplus (%), energy storage efficiency (%), thermal transmittance-u-value (w/m^{2}k) and accuracy of energy demand and generation (%). Moreover, project alternatives are Solar-Powered Residential Complex (SPRC), Vertical Urban Farming Tower (VUFT), Net-Positive Educational Campus (NPEC), Zero-Carbon Retail Center (ZRC), Industrial Energy Hub (IEH), Floating Solar Office Building (FSOB), Eco-Retreat and Resort (ERR) and Energy-Positive Hospital (EPH). After these definitions and evaluations, Eq. (5) calculates the entropy values. Table 3 exhibits the entropy values of the criteria.

After that, Eq. (6) is used to compute the information gain values. Table 4 illustrates the information gain values of EPP split by project factors.

As seen in Table 4, F1 and F2 have the highest information gain value in the project factors for EPP. So, it is seen that F1 and F2 have the most influential project input for EPP. Similarly, other entropy and information gain values are computed for the other criteria split by the inputs. Afterwards, the information gains for each input of the criteria are obtained. Tablo 5 shows the results.

In Table 5, the information gains are shown by inputs on the criteria. According to the information gains, F1 and F3 have the highest value for EPP, F4 is the best project specification for TI, and F3 has the most influential input for UHM, and F4 has the best information gain value for CSS. The scales with the highest positive values are selected for the most influential project specifications. For instance, F1 with more than 20 % and F3 with less than 15 % have the highest positive assessments in the initial expert review for EPP. So, the projects that have F1 with more than 20 % and F3 with less than 15 % are selected for the most relevant projects in terms of EPP. Similarly, the scales of the other most relevant projects inputs with the highest positive assessments are detected as F4 with more than 90 % for TI, F3 with less than 15 % for UHM, F4 with more than 90 % for CSS. Based on these information gain-based rules, the final most relevant project alternatives are defined as NPEC matching three inputs; ERR and EPH with 2 relevant project factor specifications. FSOB and VUFT have one relevant project factor. So, VUFT, NPEC, FSOB, ERR, and EPH are selected as the most relevant project alternatives for energy positive buildings investments based on information gain rules.

4.3. Creating the balanced evaluation matrices by Q-learning

After the number of alternatives is reduced to the desired level, evaluations from three experts are collected according to the scale in Table 1. Table A1 summarizes the evaluation of criteria relation according to experts. Similarly, Table A2 shares the evaluation of project alternatives according to the three experts. The evaluations of the experts are converted to the MFNs and the evaluations of first expert are defined as initial fuzzy Q matrix since the first expert is lead expert and it is compared with the evaluations of other experts by the pairwise comparison. The weight values of the other experts are determined as the fcr_r among the experts. Eq. (7) is used. Table A3 displays the reward degrees for relation matrix. Similarly, Eq. (7) is used in the decision matrix. Then, Eq. (8) is used, and the

Table 2
Project specifications and the initial criteria review by the lead expert.

Project Alternatives	Inputs (Project factors)				Outputs (Lead expert review for the criteria)			
	F1	F2	F3	F4	EPP	TI	UHM	CSS
SPRC	15	85	15	90	Significant	Significant	Significant	High
VUFT	21	80	22	85	Significant	Moderate	Significant	Significant
NPEC	25	92	12	92	High	High	High	High
ZRC	12	88	18	87	Moderate	Significant	Moderate	Significant
IEH	18	85	20	88	Significant	Significant	Significant	Significant
FSOB	22	82	16	86	Significant	Moderate	Significant	Significant
ERR	30	88	14	90	High	Significant	High	Significant
EPH	10	90	13	95	Moderate	High	High	High

Table 3
The entropies of the criteria.

Linguistic Scales/Criteria	Probability Degrees					Entropies
	Negligible	Low	Moderate	Significant	High	
EPP	.000	.000	.250	.500	.250	1.500
TI	.000	.000	.250	.500	.250	1.500
UHM	.000	.000	.125	.500	.375	1.406
CSS	.000	.000	.000	.625	.375	.954

Table 4
The G values of EPP split by project factors.

Linguistic Scales/Factor Degrees	Probability Degrees					Entropy	Information Gain
	Negligible	Low	Moderate	Significant	High		
0–10	.000	.000	1.000	.000	.000	.000	.750
10–20	.000	.000	.250	.750	.000	.811	
21 and more	.000	.000	.000	.333	.667	.918	
Linguistic Scales/Factor Degrees	Probability Degrees					Entropy	Information Gain
	Negligible	Low	Moderate	Significant	High		
0–80	.000	.000	.000	1.000	.000	.000	.406
80–90	.000	.000	.333	.500	.167	1.459	
91 and more	.000	.000	.000	.000	1.000	.000	
Linguistic Scales/Factor Degrees	Probability Degrees					Entropy	Information Gain
	Negligible	Low	Moderate	Significant	High		
0–14	.000	.000	.333	.000	.667	.918	.750
15–20	.000	.000	.250	.750	.000	.811	
21 and more	.000	.000	.000	1.000	.000	.000	
Linguistic Scales/Factor Degrees	Probability Degrees					Entropy	Information Gain
	Negligible	Low	Moderate	Significant	High		
0–85	.000	.000	.000	1.000	.000	.000	.393
86–90	.000	.000	.200	.600	.200	1.371	
91 and more	.000	.000	.500	.000	.500	1.000	

penalty degree is obtained. The weight of the lead expert is considered as a penalty factor. In that case, Table A4 gives information about the penalty degrees for decision matrix. Similarly, Eq. (8) is used for the decision matrix. After that, Eq. (9) uses for updating of the MF evaluation matrices. Table A5 summarizes the updated evaluations of relation matrices. Similarly, Eq. (9) is used for the decision matrix. Later, Eq. (10) is checked. Table A6 shares the absolute difference for relation matrix in the first iteration. Similarly, Eq. (10) is checked for the decision matrix. As a result of the fifth update, the condition for the relation matrix is satisfied. Table A7 summarizes the absolute differences calculated as a result of each iteration for relation matrix. Similarly, at the end of the fifth update, the condition for the decision matrix is satisfied. Table A8 summarizes the absolute differences calculated because of each iteration for decision matrix. Thus, stable fuzzy evaluation matrices are obtained. Table A9 shows the elements of stable relation fuzzy evaluation matrix. Table 6 gives the elements of stable decision fuzzy evaluation matrix, similarly.

4.4. Weighting of the criteria

The average of the matrices is calculated by Eq. (11). Thus, the relation matrix shown by Eq. (12) is obtained. Table A10 presents the averaged fuzzy values for the relation. Each row in RM is defined as a vector. In other words, 4 vectors are constructed. The magnitude of these vectors is 3. Eq. (13) defines the vectors generated from the RM. Table A11 shares the vectors. Then, Eq. (14) allows the calculation of the angle between the vectors. Table A12 indicates the angles for the relation matrix. Eq. (15) shows the obtaining of normalized angles according to various shapes and Table A13 exhibits the results of the piecewise function. Eq. (16) calculates the rp values and Table A14 gives the matrix formed by Eq. (17) for Shp_1. After this stage, Eqs. (18) and (19) are used to obtain the iterative state vectors. Since it is seen that the condition in Eq. (20) is satisfied at the end of the sixth iteration, Table A15 tabulates the calculations of the iterations. Once the stabilized state vectors are obtained, Eq. (21) is used, and the weights of the criteria are computed. Table 7 reports the order of priority of the criteria according to the various shapes and expert weights.

In Table 7, the priority results are the same for different expert weights. Expert 1 has the highest experience in the industry, so we define the weights of the experts for the base scenario as expert 1: 0.5; expert 2: 0.25; expert 3: 0.25. Also, we define 2 different scenarios of the expert weights for the robustness check. The results demonstrate that the weighting rankings are coherent for different weighting scenarios of the experts.

4.5. Ranking of the projects

The average of the matrices is calculated by Eq. (11). Thus, the decision matrix shown by Eq. (22) is obtained. Table A16 presents

Table 5
The information gain values for the project factors of the criteria.

Annual Energy Surplus (%)												
	EPP			TI			UHM			CSS		
Factor Degrees	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain
0–10	.000	.750	.750	.000	1.000	.500	.000	.750	.656	.000	.750	.204
10–20	.811			.811			.811			.811		
21 and more	.918			1.585			.918			.918		
Energy Storage Efficiency (%)												
	EPP			TI			UHM			CSS		
Factor Degrees	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain
0–80	.000	1.094	.406	.000	.939	.561	.000	1.094	.311	.000	.689	.266
80–90	1.459			1.252			1.459			.918		
91 and more	.000			.000			.000			.000		
Thermal transmittance-U-value (W/m^2K)												
	EPP			TI			UHM			CSS		
Factor Degrees	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain
0–14	.918	.750	.750	.918	.750	.750	.000	.406	1.000	.918	.750	.204
15–20	.811			.811			.811			.811		
21 and more	.000			.000			.000			.000		
Accuracy of energy demand and generation (%)												
	EPP			TI			UHM			CSS		
Factor Degrees	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain	Entropy	Overall Entropy	Information Gain
0–85	.000	1.107	.393	.000	.451	1.049	.000	.857	.549	.000	.451	.503
86–90	1.371			.722			1.371			.722		
91 and more	1.000			.000			.000			.000		

Table 6
The elements of the stable matrix for decision.

Expert 1	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.80,.15,.05)	(.80,.15,.05)	(.60,.30,.10)	(.80,.15,.05)
NPEC	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
FSOB	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)
ERR	(.80,.15,.05)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
EPH	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)
Expert 2	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.85,.12,.03)	(.74,.20,.07)	(.71,.22,.07)	(.85,.12,.03)
NPEC	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.85,.12,.03)
FSOB	(.84,.13,.03)	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)
ERR	(.74,.20,.07)	(.95,.05,.00)	(.95,.05,.00)	(.95,.05,.00)
EPH	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)
Expert 3	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
NPEC	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.80,.15,.05)
FSOB	(.95,.05,.00)	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)
ERR	(.95,.05,.00)	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)
EPH	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)

the averaged fuzzy values for the decision values. The weight values are used and a weighted decision matrix is created. Similar to the cognitive maps method, the normalization process is applied. As a result of the normalization process, the final decision matrix shown in Eq. (23) is obtained. Table A17 shows the elements of final decision matrix for Shp_1. Eqs. (24)-(27) are applied iteratively until the condition in Eq. (28) is met. The results in five iterations are summarized in Table A18. The average of the positions in the last iteration is determined. The average values of the projects are equal to 0.1562, 0.1560, 0.1524, 0.1440, and 0.1431 respectively. So, the ranking results are given in descending order as SPRC, VUFT, NPEC, ZRC, IEH. Table 8 reports the results of ranking of the alternatives according to the various shapes.

4.6. Comparative and sensitivity analysis

For robustness and sensitivity analysis of the ranking results, the analyses are repeated using a second method with minimal changes in weights. Analysis is performed with minimal changes such as 1 %, 2 % etc. in the criteria weights. The ARAS method is preferred as the second method. All results are visually shared in Fig. 2.

As can be seen from Fig. 2, the results are robust to method and weight changes.

5. Discussion

The results of the analysis show that the most important factor affecting energy-positive building investments is the use of high-performance materials. The long-term economic advantages offered by high-performance materials contribute to the preference for such projects. Furthermore, these materials require less maintenance, making them a preferred choice for energy-positive building projects. In addition, the long-term energy savings contribute to lower operating costs. Therefore, energy-positive building projects become more reliable, sustainable, and profitable options. Dinçer et al. analyzed the performance of European eco-management for the environmental friendliness of energy investments. It is emphasized that the material used is important in energy investments and efficiency. Bahtiar et al. (2023) examined the use of sustainable materials for green buildings. It is concluded that the quality of the materials used significantly affects energy efficiency.

Technological infrastructure is the second most important criterion affecting energy-positive building investments. A strong technological infrastructure is a factor that increases the profitability and efficiency of investors. The use of advanced state-of-the-art technology reduces energy production costs. Therefore, it becomes more attractive for investors. Furthermore, technological infrastructure plays an important role in energy-positive building design that reduces carbon emissions. The investment decisions of environmentally conscious investors can be shaped according to these considerations. Ahmad et al. (2024) conducted a study on the adoption of green buildings in Qatar. It is stated that technological infrastructure is a deficiency in the adoption of green buildings. Artie et al. carried out a study aimed at the development of green and smart buildings. It is emphasized that technological infrastructure is needed for an optimized solar tracking system.

The findings show that the most important investment alternative is the vertical urban farming tower. A vertical urban farming tower is a type of building that involves optimizing vertical structures for agricultural production. These buildings have the advantage of utilizing renewable energy systems such as solar energy and wind turbines. They are also suitable for waste management and water recycling technologies. They align with global priorities such as food security, energy efficiency, and sustainability. It is attractive for investors because of its long-term return potential. Kabir et al. (2023) examined technological trends in vertical farming. It is argued that vertical farming is a promising solution for food security and sustainability. The second most important alternative is the net-positive educational campus. Net-positive educational campuses are important structures that aim for energy efficiency. In these buildings, it is possible to store and sell surplus energy. This can be effective in the investment decision. In addition, energy efficiency contributes to the reduction of costs. As it is an environmentally friendly model, it increases reputation and brand value. Li et al. (2024)

Table 7
The priority of the criteria according to various shapes and expert weights.

Expert weights (Base Scenario) (Expert 1:0.5; Expert 2:0.25; Expert 3:0.25)					
$fcr_{l=0.1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=0.5}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
Expert weights (Scenario 2) (Expert 1:0.5; Expert 2:0.30; Expert 3:0.20)					
$fcr_{l=0.1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=0.5}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
Expert weights (Scenario 3) (Expert 1:0.5; Expert 2:0.20; Expert 3:0.30)					
$fcr_{l=0.1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=0.5}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3
$fcr_{l=1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
EPP	4	4	4	4	4
TI	2	2	2	2	2
UHM	1	1	1	1	1
CSS	3	3	3	3	3

analyzed the transformation of campuses in the smart city development process. It is emphasized that green campuses have a significant impact on energy efficiency.

6. Conclusion

This study presents a novel decision-making model to identify appropriate investment strategies for energy-positive building projects. The study provides a comprehensive approach to optimize these investments by integrating different techniques, such as information gain-based attribute selection, q-learning and MF cognitive maps. The findings highlight the critical importance of using high-performance materials and incorporating technological advancements in energy-positive building projects. The ranking results indicate that the vertical urban farming tower and the net-positive educational campus are the most critical investment alternatives. These findings provide valuable insights for policymakers and investors. Hence, it can be possible to allocate resources effectively. The flexible structure of the model is one of the important contributions of the study. The proposed model can be applied to different energy-positive building projects. The MF MOPSO technique used in the alternative ranking is a dynamic approach. In this way, it is much easier to adapt to the uncertainties that arise. On the other hand, the criteria and alternatives used in the model are quite suitable

Table 8
The ranks of the projects according to various shapes.

$fcr_{l=0.1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
VUFT	1	1	1	1	1
NPEC	2	2	2	2	2
FSOB	3	3	3	3	3
ERR	4	4	4	4	4
EPH	5	5	5	5	5
$fcr_{l=0.5}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
VUFT	1	1	1	1	1
NPEC	2	2	2	2	2
FSOB	3	3	3	3	3
ERR	4	4	4	4	4
EPH	5	5	5	5	5
$fcr_{l=1}$	**Shp_1**	**Shp_2**	**Shp_3**	**Shp_4**	**Shp_5**
VUFT	1	1	1	1	1
NPEC	2	2	2	2	2
FSOB	3	3	3	3	3
ERR	4	4	4	4	4
EPH	5	5	5	5	5

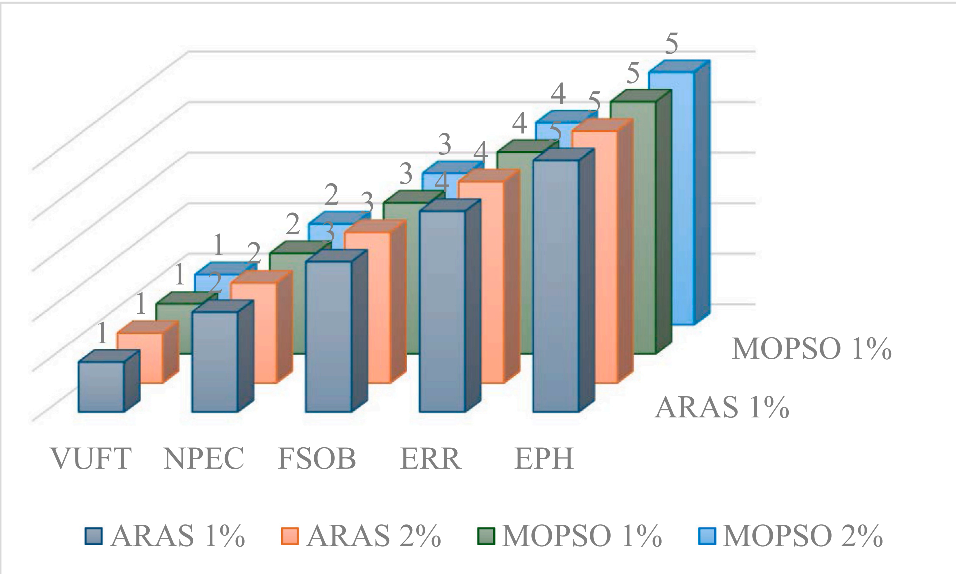

Fig. 2. Comparative and Sensitivity Analysis.

for real-world conditions. In the real world, investment decisions are always made with uncertainties and variable parameters. The model is designed to minimize uncertainties in investment processes. Thus, it offers dynamic and reliable solutions to decision makers.

Information Gain-Based Prioritization reduces project alternatives from eight to five, with energy production potential (information gain: 0.750) and the use of high-performance materials (information gain: 1.000) identified as the most critical factors. This reduction ensures focus on the most impactful projects. Q-Learning for Expert Consensus balances expert evaluations, achieving stable decision matrices after five iterations (convergence tolerance: 0.02). This process dynamically weights experts based on experience, minimizing subjectivity. MF Cognitive Maps for Criterion Weighting shows that the use of high-performance materials (weight: 0.256) and technological infrastructure (weight: 0.253) are prioritized, validated across multiple molecular geometry shapes (linear, trigonal, tetrahedral, etc.). MF-MOPSO for Ranking gives information about the vertical urban farming tower (score: 0.1562) and net-positive educational campus (score: 0.1560) rank highest, with results consistent across all tested shapes. Comparative analysis with the ARAS method confirms robustness, showing minimal deviation (<2 %) under weight perturbations.

The weighting of performance indicators and the ranking of alternatives in the study are largely based on expert opinions. It may create subjective differences in the results depending on the perspective of the selected experts. It can be considered as the biggest limitation of the proposed model. Energy-positive building projects are affected by changing economic, technological and environmental conditions. However, the effects of such dynamic variables on investment decisions are not considered in detail in the model. A more realistic analysis can be made by taking dynamic issues into account in future studies. Thus, the conditions affecting investment decisions can be determined more clearly. Another important limitation is that the study does not conduct an analysis for any country group. In this context, an analysis for developing or developed country groups would allow for the determination of more specific investment strategies. One of the limitations of this study is that the proposed model has been tested on a relatively small set of criteria and project alternatives. This implementation provides a controlled evaluation of the methodology. However, it does not fully examine the complexities of large-scale investment decisions in energy-positive building projects. By considering these issues, future studies can further investigate the model's scalability. For this purpose, more extensive datasets can be taken into consideration with a broader range of investment criteria and project alternatives.

CRediT authorship contribution statement

Gang Kou: Visualization, Data curation, Methodology, Formal analysis, Writing – review & editing, Resources, Validation, Supervision, Conceptualization, Investigation, Writing – original draft, Software, Funding acquisition, Project administration. **Ümit Hacıoğlu:** Investigation, Formal analysis, Software, Validation, Project administration, Writing – original draft, Supervision, Data curation, Conceptualization, Writing – review & editing, Methodology, Resources, Funding acquisition. **Serkan Eti:** Validation, Writing – review & editing, Investigation, Resources, Formal analysis, Conceptualization, Software, Visualization, Supervision, Project administration, Data curation, Funding acquisition, Writing – original draft, Methodology. **Hasan Dinçer:** Visualization, Funding acquisition, Formal analysis, Resources, Investigation, Writing – review & editing, Project administration, Software, Methodology, Conceptualization, Supervision, Data curation, Validation, Writing – original draft. **Serhat Yüksel:** Funding acquisition, Writing – review & editing, Supervision, Data curation, Project administration, Formal analysis, Visualization, Resources, Conceptualization, Validation, Methodology, Writing – original draft, Software, Investigation. **Yaşar Gökalp:** Data curation, Resources, Investigation, Project administration, Validation, Funding acquisition, Writing – review & editing, Visualization, Supervision, Conceptualization, Methodology, Formal analysis.

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.

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Appendix

Table A1
The Evaluations of Criteria Relation

Expert 1	EPP	TI	UHM	CSS
EPP		H	S	M
TI	H		S	S
UHM	S	S		S
CSS	H	S	H	
Expert 2	EPP	TI	UHM	CSS
EPP		M	S	M
TI	M		S	S
UHM	S	M		S
CSS	S	S	H	
Expert 3	EPP	TI	UHM	CSS
EPP		H	S	M
TI	H		S	S
UHM	S	S		H
CSS	S	S	H	

Table A2
The Evaluations of the Project Alternatives Relation

Expert 1	EPP	TI	UHM	CSS
VUFT	S	S	M	S
NPEC	H	S	S	S
FSOB	H	S	H	S
ERR	S	H	H	H
EPH	S	H	S	H

(*continued on next page*)

Table A2 (*continued*)

Expert 2	EPP	TI	UHM	CSS
VUFT	H	M	H	H
NPEC	H	S	S	H
FSOB	M	S	H	S
ERR	M	H	H	H
EPH	S	H	S	H
Expert 3	EPP	TI	UHM	CSS
VUFT	H	S	S	S
NPEC	H	S	S	S
FSOB	H	H	S	S
ERR	H	H	S	S
EPH	S	H	S	S

Table A3
Reward Degrees for Relation Matrix

Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(−.09,.06,.03)	(.00,.00,.00)	(.00,.00,.00)
TI	(−.09,.06,.03)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
UHM	(.00,.00,.00)	(−.05,.04,.01)	(.00,.00,.00)	(.00,.00,.00)
CSS	(−.04,.03,.01)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
Expert 1-Expert 3	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
TI	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
UHM	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.04, −.03, −.01)
CSS	(−.04,.03,.01)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)

Table A4
Penalty Degree for Decision Matrix

Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.18, −.13, −.05)	(.00,.00,.00)	(.00,.00,.00)
TI	(.18, −.13, −.05)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
UHM	(.00,.00,.00)	(.10, −.08, −.03)	(.00,.00,.00)	(.00,.00,.00)
CSS	(.08, −.05, −.03)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
Expert 1-Expert 3	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
TI	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)
UHM	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)	(−.08,.05,.03)
CSS	(.08, −.05, −.03)	(.00,.00,.00)	(.00,.00,.00)	(.00,.00,.00)

Table A5
The Updated Evaluations for Relations

Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.92,.07,.01)	(.80,.15,.05)	(.60,.30,.10)
TI	(.92,.07,.01)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.79,.16,.05)	(.00,.00,.00)	(.80,.15,.05)
CSS	(.94,.06,.00)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)
Expert 1-Expert 3	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.95,.05,.00)	(.80,.15,.05)	(.60,.30,.10)
TI	(.95,.05,.00)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)	(.81,.14,.05)
CSS	(.94,.06,.00)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)

Table A6
Absolute Difference for Relation Matrix (First Iteration)

Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.026,.019,.008)	(.000,.000,.000)	(.000,.000,.000)
TI	(.026,.019,.008)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.015,.011,.004)	(.000,.000,.000)	(.000,.000,.000)
CSS	(.011,.008,.004)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)

(*continued on next page*)

Table A6 (*continued*)

Expert 1-Expert 3	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
TI	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.011,.008,.004)
CSS	(.011,.008,.004)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)

Table A7
The Iterative Results for Relation Matrix Between First and Second Experts

Iteration 2				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.024,.017,.007)	(.000,.000,.000)	(.000,.000,.000)
TI	(.024,.017,.007)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.014,.010,.003)	(.000,.000,.000)	(.000,.000,.000)
CSS	(.010,.007,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 3				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.022,.016,.006)	(.000,.000,.000)	(.000,.000,.000)
TI	(.022,.016,.006)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.013,.010,.003)	(.000,.000,.000)	(.000,.000,.000)
CSS	(.010,.006,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 4				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.021,.015,.006)	(.000,.000,.000)	(.000,.000,.000)
TI	(.021,.015,.006)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.012,.009,.003)	(.000,.000,.000)	(.000,.000,.000)
CSS	(.009,.006,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 5				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.000,.000,.000)	(.019,.014,.005)	(.000,.000,.000)	(.000,.000,.000)
TI	(.019,.014,.005)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
UHM	(.000,.000,.000)	(.011,.008,.003)	(.000,.000,.000)	(.000,.000,.000)
CSS	(.008,.005,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)

Table A8
The Iterative Results for Decision Matrix Between First and Second Experts

Iteration 2				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.010,.007,.003)	(.014,.010,.003)	(.024,.017,.007)	(.010,.007,.003)
NPEC	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.010,.007,.003)
FSOB	(.024,.017,.007)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
ERR	(.014,.010,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
EPH	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 3				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.010,.006,.003)	(.013,.010,.003)	(.022,.016,.006)	(.010,.006,.003)
NPEC	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.010,.006,.003)
FSOB	(.022,.016,.006)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
ERR	(.013,.010,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
EPH	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 4				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.009,.006,.003)	(.012,.009,.003)	(.021,.015,.006)	(.009,.006,.003)
NPEC	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.009,.006,.003)
FSOB	(.021,.015,.006)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
ERR	(.012,.009,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
EPH	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Iteration 5				
Expert 1-Expert 2	**EPP**	**TI**	**UHM**	**CSS**
VUFT	(.008,.005,.003)	(.011,.008,.003)	(.019,.014,.005)	(.008,.005,.003)
NPEC	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.008,.005,.003)
FSOB	(.019,.014,.005)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
ERR	(.011,.008,.003)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
EPH	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)

Table A9
The Elements of the Stable Matrix for Relation

Expert 1	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.95,.05,.00)	(.80,.15,.05)	(.60,.30,.10)
TI	(.95,.05,.00)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)	(.80,.15,.05)
CSS	(.95,.05,.00)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)
Expert 2	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.84,.13,.03)	(.80,.15,.05)	(.60,.30,.10)
TI	(.84,.13,.03)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.74,.20,.07)	(.00,.00,.00)	(.80,.15,.05)
CSS	(.90,.08,.02)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)
Expert 3	**EPP**	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.95,.05,.00)	(.80,.15,.05)	(.60,.30,.10)
TI	(.95,.05,.00)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.80,.15,.05)	(.00,.00,.00)	(.95,.05,.00)
CSS	(.80,.15,.05)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)

Table A10
Averaged Fuzzy Evaluations for Relation

	EPP	**TI**	**UHM**	**CSS**
EPP	(.00,.00,.00)	(.91,.08,.01)	(.80,.15,.05)	(.60,.30,.10)
TI	(.91,.08,.01)	(.00,.00,.00)	(.80,.15,.05)	(.80,.15,.05)
UHM	(.80,.15,.05)	(.78,.17,.06)	(.00,.00,.00)	(.85,.12,.03)
CSS	(.88,.09,.02)	(.80,.15,.05)	(.95,.05,.00)	(.00,.00,.00)

Table A11
The Vectors for RM

	MF-Vecs
u_1	[(.91,.08,.01), (.80,.15,.05), (.60,.30,.10)]
u_2	[(.91,.08,.01), (.80,.15,.05), (.80,.15,.05)]
u_3	[(.80,.15,.05), (.78,.17,.06), (.85,.12,.03)]
u_4	[(.88,.09,.02), (.80,.15,.05), (.95,.05,.00)]

Table A12
The Angles for RM

	$\boldsymbol{\theta_{u_1}}$	$\boldsymbol{\theta_{u_2}}$	$\boldsymbol{\theta_{u_3}}$	$\boldsymbol{\theta_{u_4}}$
θ_{u_1}		.171	.246	.289
θ_{u_2}	.171		.103	.119
θ_{u_3}	.246	.103		.084
θ_{u_4}	.289	.119	.084	

Table A13
The Normalized Angles

Shp_1	$\boldsymbol{norm(\theta_{u_1})}$	$\boldsymbol{norm(\theta_{u_2})}$	$\boldsymbol{norm(\theta_{u_3})}$	$\boldsymbol{norm(\theta_{u_4})}$
$norm(\theta_{u_1})$	.000	.054	.078	.092
$norm(\theta_{u_2})$	.054	.000	.033	.038
$norm(\theta_{u_3})$	.078	.033	.000	.027
$norm(\theta_{u_4})$	.092	.038	.027	.000
Shp_2	$\boldsymbol{norm(\theta_{u_1})}$	$\boldsymbol{norm(\theta_{u_2})}$	$\boldsymbol{norm(\theta_{u_3})}$	$\boldsymbol{norm(\theta_{u_4})}$
$norm(\theta_{u_1})$	.000	.081	.117	.138
$norm(\theta_{u_2})$	.081	.000	.049	.057
$norm(\theta_{u_3})$	.117	.049	.000	.040
$norm(\theta_{u_4})$	.138	.057	.040	.000
Shp_3	$\boldsymbol{norm(\theta_{u_1})}$	$\boldsymbol{norm(\theta_{u_2})}$	$\boldsymbol{norm(\theta_{u_3})}$	$\boldsymbol{norm(\theta_{u_4})}$
$norm(\theta_{u_1})$	.000	.089	.129	.151
$norm(\theta_{u_2})$	.089	.000	.054	.062

(*continued on next page*)

Table A13 (*continued*)

Shp_1	$norm(\theta_{u_1})$	$norm(\theta_{u_2})$	$norm(\theta_{u_3})$	$norm(\theta_{u_4})$
$norm(\theta_{u_3})$	.129	.054	.000	.044
$norm(\theta_{u_4})$	.151	.062	.044	.000
Shp_4	$norm(\theta_{u_1})$	$norm(\theta_{u_2})$	$norm(\theta_{u_3})$	$norm(\theta_{u_4})$
$norm(\theta_{u_1})$	.000	.093	.134	.158
$norm(\theta_{u_2})$	.093	.000	.056	.065
$norm(\theta_{u_3})$	.134	.056	.000	.046
$norm(\theta_{u_4})$	.158	.065	.046	.000
Shp_5	$norm(\theta_{u_1})$	$norm(\theta_{u_2})$	$norm(\theta_{u_3})$	$norm(\theta_{u_4})$
$norm(\theta_{u_1})$	.000	.109	.156	.184
$norm(\theta_{u_2})$	.109	.000	.065	.076
$norm(\theta_{u_3})$	.156	.065	.000	.053
$norm(\theta_{u_4})$	.184	.076	.053	.000

Table A14
The Normalization of RM for Linear

	EPP	**TI**	**UHM**	**CSS**
EPP	0	.135	.094	.080
TI	.135	0	.224	.193
UHM	.094	.224	0	.274
CSS	.080	.193	.274	0

Table A15
The Iterative Results

	$A(0)$	$A(1)$	$f(A(1))$	$f(A(2))$	$f(A(3))$	$f(A(4))$	$f(A(5))$	$f(A(6))$	**Weight**
EPP	1	.309	.577	.549	.545	.545	.545	.545	.238
TI	1	.552	.635	.585	.579	.578	.578	.578	.253
UHM	1	.592	.644	.591	.585	.584	.584	.584	.256
CSS	1	.547	.633	.585	.579	.578	.578	.578	.253

Table A16
The Averaged Fuzzy Evaluations for Decision

	EPP	**TI**	**UHM**	**CSS**
VUFT	(.87,.11,.03)	(.78,.17,.06)	(.70,.22,.07)	(.82,.14,.04)
NPEC	(.95,.05,.00)	(.80,.15,.05)	(.80,.15,.05)	(.82,.14,.04)
FSOB	(.91,.08,.01)	(.85,.12,.03)	(.90,.08,.02)	(.80,.15,.05)
ERR	(.83,.13,.04)	(.95,.05,.00)	(.90,.08,.02)	(.90,.08,.02)
EPH	(.80,.15,.05)	(.95,.05,.00)	(.80,.15,.05)	(.90,.08,.02)

Table A17
The Elements of F for Linear Shape

	VUFT	**NPEC**	**FSOB**	**ERR**	**EPH**
VUFT		.138	.080	.066	.077
NPEC	.138		.138	.074	.072
FSOB	.080	.138		.105	.079
ERR	.066	.074	.105		.171
EPH	.077	.072	.079	.171	

Table A18
The Iteratively Results of MOPSO

	VUFT $((V_1)(1))$	NPEC $((V_2)(1))$	FSOB $((V_3)(1))$	ERR $((V_4)(1))$	EPH $((V_5)(1))$	VUFT $((P_1)(1))$	NPEC $((P_2)(1))$	FSOB $((P_3)(1))$	ERR $((P_4)(1))$	EPH $((P_5)(1))$	$((P_{gb})(1))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
VUFT		.005	.079	.099	.087	.000	.142	.159	.164	.165	.14	-
NPEC	.004		-.007	.079	.090	.142	.000	.131	.153	.162	.14	-
FSOB	.080	.001		.043	.075	.159	.139	.000	.147	.153	.14	-
ERR	.134	.121	.092		.006	.200	.195	.197	.000	.177	.17	-
EPH	.120	.141	.119	-.008		.198	.213	.197	.164	.000	.17	-
	VUFT $((V_1)(2))$	NPEC$((V_2)(2))$	FSOB $((V_3)(2))$	ERR $((V_4)(2))$	EPH $((V_5)(2))$	VUFT $((P_1)(2))$	NPEC $((P_2)(2))$	FSOB $((P_3)(2))$	ERR $((P_4)(2))$	EPH $((P_5)(2))$	$((P_{gb})(2))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
VUFT		.00	.02	.02	.02	.00	.14	.17	.17	.16	.14	.000
NPEC	.00		.00	.04	.03	.14	.00	.14	.17	.17	.14	.000
FSOB	.03	.00		.02	.02	.17	.14	.00	.15	.16	.14	.000
ERR	.05	.06	.03		.00	.22	.22	.21	.00	.18	.17	.002
EPH	.04	.06	.03	-.01		.22	.22	.22	.17	.00	.17	.003
	VUFT $((V_1)(3))$	NPEC $((V_2)(3))$	FSOB $((V_3)(3))$	ERR $((V_4)(3))$	EPH $((V_5)(3))$	VUFT $((P_1)(3))$	NPEC $((P_2)(3))$	FSOB $((P_3)(3))$	ERR $((P_4)(3))$	EPH $((P_5)(3))$	$((P_{gb})(3))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
VUFT		.01	.00	.00	.00	.00	.15	.17	.17	.16	.17	.03
NPEC	.00		.01	.01	.01	.15	.00	.15	.17	.17	.17	.03
FSOB	.01	.00		.01	.00	.17	.15	.00	.16	.16	.17	.03
ERR	.01	.02	.01		.01	.22	.22	.21	.00	.19	.22	.05
EPH	.01	.02	.01	.00		.22	.22	.22	.19	.00	.22	.05
	VUFT $((V_1)(4))$	NPEC $((V_2)(4))$	FSOB $((V_3)(4))$	ERR $((V_4)(4))$	EPH $((V_5)(4))$	VUFT $((P_1)(4))$	NPEC $((P_2)(4))$	FSOB $((P_3)(4))$	ERR $((P_4)(4))$	EPH $((P_5)(4))$	$((P_{gb})(4))$	$((P_{gb})(t)) - ((P_{gb})(t-1))$
VUFT		-.01	-.10	-.12	-.10	.00	.17	.17	.17	.16	.17	.00
NPEC	.00		-.01	-.11	-.11	.17	.00	.17	.17	.17	.17	.00
FSOB	-.10	.00		-.06	-.10	.17	.17	.00	.16	.16	.17	.00
ERR	-.18	-.17	-.12		-.01	.22	.22	.21	.00	.22	.22	.00
EPH	-.16	-.17	-.16	-.01		.22	.22	.22	.22	.00	.22	.00

Data availability

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

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