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Multicriteria decision-making framework for robust energy management AI solutions

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ABSTRACT

In recent years, global attention has been shifted toward energy issues, prompting significant support from major countries toward nearly zero-energy structures. However, this transition faces challenges, particularly regarding the financial implications of implementation despite diverse methodologies. The emergence of artificial intelligence (AI) has catalyzed advancements in energy conservation and management, leading to the development of numerous smart energy management systems leveraging the internet of things and AI methodologies. Various machine learning (ML) models have been utilized for energy-saving and consumption prediction solutions, posing challenges in selecting the most effective model. Multicriteria decision-making (MCDM) models offer a solution to this challenge and have been applied across domains, including energy management. This study aims to utilize MCDM approaches, specifically the fuzzy-weighted zero-inconsistency (FWZIC) and combinative distance-based assessment (CODAS) methods, to select the best energy management ML model. The study used data for eight ML alternatives based on the assessments by three field experts with respect to five criteria. The results of the criteria evaluation weights indicate that robustness (C_1) received the highest criterion weight with a value of *0.298*. The results of the alternative evaluation indicated the hybrid artificial neural network (A_1) as the best model for performance. Additionally, a comparison analysis was performed between FWZIC and various criteria weighting methods, as well as between CODAS and different alternative ranking methods. This framework enables decisionmakers to consider an AI solution that optimizes for accuracy, costs, and resilience in a move towards zero-energy infrastructure.

1. Introduction

In recent years and in light of worsening environmental crises and stringent sustainability objectives, the world has accelerated its momentum towards close to zero-energy buildings [23]. The current shift has emerged, in part, due to the legitimate fear to reduce carbon emissions and to maximize the use of energy in industrial, residential, and commercial applications [10,13]. However, there are real and continued economic and technical challenges associated with implementing these changes. For instance, the effectiveness of introducing advanced technologies into the existing infrastructures usually requires high initial investment and operational uncertainties [11]. These difficulties highlight the importance of artificial intelligence (AI) and machine learning (ML) as the next-generation energy management system that can efficiently handle the demand forecasting, resource allocation, and real-time monitoring (Z [9].).

The rise of AI techniques has accelerated the creation of various ML models focused on energy efficiency. Initial methods, focused on artificial neural networks (ANNs) and support vector machines (SVMs), where; ANN yielded interesting results predicting energy loads [25,28].

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Later developments included hybrid designs like combining CNNs with RNNs to handle time-series energy data [7] and RL systems for adaptive smart grid management [31]. ML modelling paradigms such as hybrid ML-RL systems [30] and IoT integrated ML models [6] have recently emerged; these exemplify the fast growing nature of this domain. Notably, the performance metrics utilized to gauge the effectiveness of these models often focus on accuracy at the expense of other essential factors such as computational efficiency, uncertainty resilience, and real-time adaptability [14,20].

Multicriteria decision-making (MCDM) models are capable of resolving the problem of selection in various domains [5,12,15]. In the literature, traditional MCDM methods, such as the technique for order preference by similarity to ideal solution (TOPSIS) and the analytical hierarchy process (AHP), have been utilized a lot for different purposes. However, these traditional models have accepted similar limitations in other disciplines. These methods have been found to exhibit limitations with respect to experts' subjective judgements and discrepancies with weights, which invariably create biased results and unstable ranks [21]. For example, AHP using pairwise comparisons introduces scaling problems and TOPSIS suffers from rank reversal when the weights of criteria changes [22,26]. Particularly, the existing research on energy management faces challenges due to the diverse range of research subjects, data structures, and learning algorithms. Also, the integration of data formats, the complexity of algorithms, and stakeholder conflict all contribute to fragmentation in energy management research. This fragmentation makes it challenging to integrate findings into comprehensive solutions for energy savings in buildings [11]. Hence, these limitations indicate the need to develop a robust MCDM framework capable of reconciling technical performance with operational viability in energy systems.

While MCDM approaches have been deployed in energy systems for technology selection and the allocation of resources, there remains limited utilization of these approaches, particularly in evaluating and reviewing ML driven energy management frameworks. In many instances, research on ML systems focuses on model validation with limited attention to the system as a whole (e.g. the integration of the IoT, robustness of algorithms, and stakeholder and developer needs in the real world). Also, currently, the literature lacks standardized evaluation frameworks, which complicates the process of selecting the optimal ML model for energy management applications. To address this gap, this work provides a systematic framework to evaluate ML models for IoT suitability with energy management systems by suggesting a comprehensive MCDM framework that incorporates both the fuzzy-weighted zero-inconsistency (FWZIC) method for the weighting of criteria and the combinative distance-based assessment (CODAS) for the ranking of alternatives. Combined with FWZIC method, which is one of the most suitable methods in minimizing weighting inconsistency through expert-derived weights [21], and CODAS, which offers two distance or dissimilarity metrics (the Euclidean and the Taxicab) to strengthen the stability of the results (Abdullah [1]). This interplay mitigates some of the major limitations of previous methods and our method provides a transparent and robust decision-making tool for determining the best ML model for energy management tasks. Using this framework, eight state-of-the-art ML approaches are assessed, including decision tree (DT) (S [18].), random forests (RF) [19], deep learning (DL) [7], hybrid ANN [17], and IoT-RNN integration [6], against five rigorously defined criteria. These criteria are robustness, feedback response, computational burden, intelligent design, and online monitoring.

These criteria, resulting from a systematic review of 32 studies [11], cater to industry priorities such as operational reliability and cost-effectiveness. The main contributions of this research include the following key points.

- A decision matrix to merge IoT-AI energy management systems with assessment parameters including computing efficiency, resilience and diversification.
- Integrating FWZIC and CODAS to address MCDM challenges in energy systems, providing stakeholders with the ability to rank models while considering the trade-offs between technical performance and practicalities.
- Developing tests based on different scenarios to evaluate how the framework can adapt to different operational contexts so that policymakers and industry practitioners can be confident of the framework's reliability. Moreover, a comparison analysis was performed between the proposed integrated model with other MCDM models.

This work bridges the gap between algorithmic innovation and real-world deployment by proposing a unified MCDM framework that is empowering decision-makers to deploy energy management interventions that are cost efficient, emission reducing and compatible with decarbonization targets. The remainder of this paper is structured as follows: Section 2 presents the methodology of the research design and development, Section 3 presents the evaluation and benchmarking results, Section 4 discusses the sensitivity analysis, Section 5 performs a comparison analysis of the proposed framework, and Section 6 concludes the research.

2. Methodology

In this section, the methodology of the study is proposed on the basis of three phases. In the first phase, the decision matrix (DM) is constructed, and the evaluation attributes are identified and compared against alternatives. The second phase involves the employment of FWZIC for criteria weighting, followed by the third phase, where CODAS is used for ranking purposes. Fig. 1 shows the phases and steps of the proposed framework.

2.1. Phase one: decision matrix construction

This section provides an overview of the DM for ML energy management methodologies. DM is constructed utilizing components of alternatives and criteria for crossover, as previously defined. The structured methodology identified five evaluation criteria from a systematic review of thirty-two studies related to ML models within energy management [11]. The ordering and rankings from the structured methodology prioritized the most significant criteria for real-world implementation. The five evaluation criteria were robustness, feedback response, computational burden, intelligent design and online monitoring. The definitions for each of these criteria can be found in Table 1. The alternatives within this case study are 8 ML methods and 5 evaluation criteria. Each alternative will be evaluated according to the evaluation criteria presented. The selected alternatives are the hybrid artificial neural network (ANN) (*A1*) [17], hybrid support vector machine (SVM) (*A2*) [25], extreme learning machine (ELM) (*A3*) [24], convolutional neural network (CNN) and recurrent neural network (RNN) (*A4*) [7], RF (*A5*) [27], reinforcement learning (RL) (*A6*) [31], hybrid ML and RL (*A7*) [30], and IoT and RNN (*A8*) [6]. This selection of ML models also provides the necessary breadth of ML model architectures for the evaluation, which makes the partnership of ML models and energy optimization robust and equitable. For example, IoT-RNN (A8) represents the rising inclusion and application of edge computing within smart grids. Also, the selected alternatives represent a proof-of-concept for the proposed framework and these alternatives can be expanded in future studies.

Each criterion was evaluated by three domain experts (>10 years of experience in AI-driven energy systems) according to their importance. Based on various prior studies of MCDM, the minimum requirement for accepted expert selection was three experts for initial validation, where three experts provided statistically consistent weights for evaluating criteria (AH [2]; Y [8,29].). The evaluations were performed through the 5-point Likert scale (Table 3) which was subsequently transformed into triangular fuzzy numbers (TFNs) to better characterize the linguistic

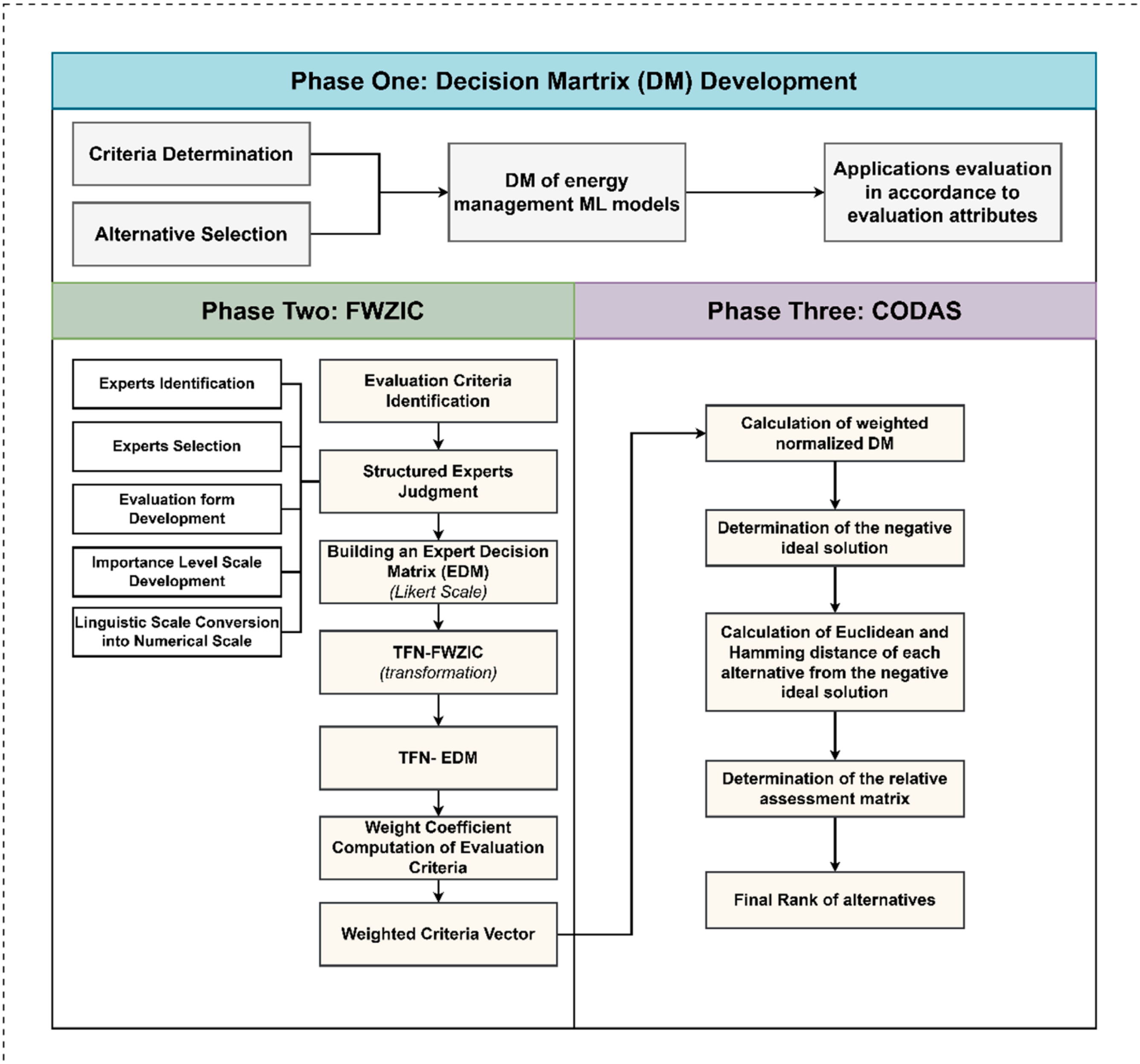

Fig. 1. Phases of the proposed framework.

uncertainties.

2.2. Phase two: development phase

The method of FWZIC is explained herein [21]. The FWZIC represents a recent addition to the arsenal of multicriteria decision-making techniques. The criteria weights should be assigned with no inconsistencies in the FWZIC. This method was designed to address the weaknesses of existing methods, e.g., AHP and BWM.

Step one: Definition of the evaluation criteria set. This step includes two processes. The initial step involves examining and presenting a predetermined set of assessment criteria. Following this, all the gathered criteria are sorted and grouped. A panel of experts is required to assess the defined and chosen criteria.

Step two: Judgment of structured experts. The assessment of the importance levels of the criteria shall be carried out by a group of three expert evaluators, chosen on the basis of their expertise in the respective study areas. The selection of three experts is consistent with the minimal requirements set out in this procedure. By means of email correspondence, the experts' interest and ability to participate in a panel are confirmed. To ensure consistency and legitimacy, an evaluation form should be drawn up for the collection of opinions from panel members that are subject to testing and assessment by specialized experts. The

Table 1
Definition of the evaluation criteria.

Criteria	Definition
C_1 (Robustness)	*The system's ability to function in uncertain conditions*
C_2 (Feedback response)	*The time delay between submitting a request and receiving a response*
C_3 (Computational burden)	*The number of resources required to perform a certain action*
C_4 (Intelligent design)	*The proper system parameters' selection for performance, reliability, and efficiency.*
C_5 (Online monitoring)	*The ability to continuously observe the performance of the system in real-time*

experts used the five-point Likert scale to classify the relative significance of each criterion using language terms. For the next analysis, these terms are converted to numerical scores, as illustrated in Table 3.

Step three: Expert decision matrix construction. A matrix of expert decisions is drawn by combining the multi-metric measurement criteria with the insights of a panel of three experts, as presented in Table 2. This process allows experts to express that all multi-metric criteria are important. For the analytical objectives set out in the proposed method, the EDM is an initial step.

Step four: Fuzzy Membership Function Application. To enhance the accuracy and analytical depth, this phase involves refining and improving the data obtained from EDMs. The use of a fuzzy membership function and derogation process is used to achieve this objective. In MCDM, TFNs are often used to address uncertainties and inconsistencies. As shown in Fig. 2, TFNs are denoted as A = (a, b, c), where a is the lower limit, b is the most likely value to occur, and c is the upper limit of the triangular distribution. TFNs are especially useful in providing estimates when obtaining precise numerical values is difficult or is not meaningful due to ambiguity. TFNs allow decision-makers to quantify and represent uncertainty or imprecision accurately while allowing a flexible and intuitive approach to the characterization of decision criteria and evaluation of alternative solutions in MCDM situations. One main advantage of using TFNs is its simplicity and theoretical clarity. Furthermore, TFNs are limitless in their computational operations, as they can be defined for addition, subtraction, multiplication, and division. In particular, TFNs are often utilized in MCDM situations to represent the importance of criteria. Decision-makers assign TFNs to each criterion to reflect their subjective assessment of its relative significance or performance concerning alternatives. For instance, a criterion expressed as 'very important' corresponds to (0.75, 0.90, 1.00), thus allowing for flexible aggregation of expert inputs while protecting the type of granularity required for high-precision weight computation. Thus, by including TFNs in their decision-making processes, decision-makers can make more informed and resilient decisions, taking into account a wider array of considerations and uncertainties.

To describe the membership function (x) of TFN A, Eq. (1) is applied:

$$\mu_A(x) = \begin{cases} 0 \; if \; x < a \\ \dfrac{x-a}{b-a} \; if \; a \leq x \leq b \\ \dfrac{c-x}{c-b} \; if \; b \leq x \leq x \\ 0 \; if \; x > c \end{cases}, \; where \; a \leq b \leq c. \tag{1}$$

Moreover, Table 3 shows the linguistic term values with TFNs.

Table 3 recommends transforming all linguistic variables into triangular fuzzy numbers (TFNs) for expert K's criteria. For instance, if an expert selected a number 4 in the Likert scale during the evaluation process, this selection will be equivalent to "Important" in the linguistic terms, which means that it will be transformed into (0.50,0.75,0.90) in the TFN terms.

Step five: Calculation of the Final Weight: During this stage, we establish the weight coefficients ($w_1, w_2 \ldots w_n$) for the assessment criteria by utilizing the fuzzified data obtained in the previous step. We employ Eq. (2), which uses TFNs in combination with the aforementioned formula, to determine the ratio of the fuzzified data.

Table 2
Expert decision matrix.

Criteria Experts	CT1	CT2	…	CTn
ET1	Imp (ET1/CT1)	Imp (ET1/CT2)	…	Imp (ET1/CTn)
ET2	Imp (ET2/CT1)	Imp (ET2/CT2)	…	Imp (ET2/CTn)
ET3	Imp (ET3/CT1)	Imp (ET3/CT2)	…	Imp (ET3/CTn)
…	…	…	…	…
ETm	Imp (ETn/CT1)	Imp (ETn/CT2)	…	Imp (ETm/CTn)

** (ETn) refers to the selected experts, (CTn) refers to the criteria, and (Imp) refers to the importance level.

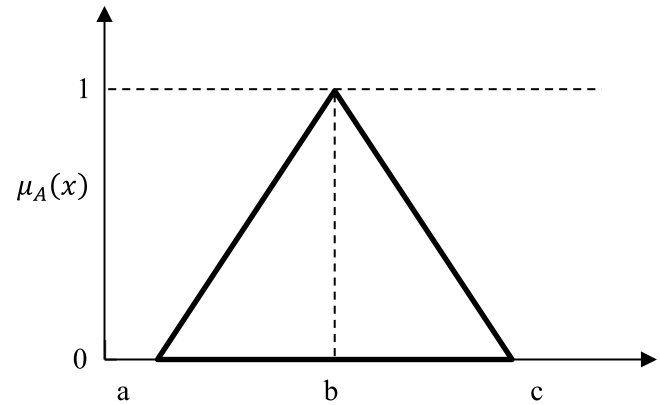

Fig. 2. Membership of TFNs.

Table 3
Linguistic terms with corresponding TFNs.

TFNs	Linguistic terms	Numerical Scoring Scale
(0.75,0.90,1.00)	Very important	5
(0.50,0.75,0.90)	Important	4
(0.30,0.50,0.75)	Moderately important	3
(0.10,0.30,0.50)	Slight important	2
(0.00,0.10,0.30)	Not important	1

$$\frac{Imp(\widetilde{E1/C1})}{\sum_{j=1}^{n} Imp(\widetilde{E1/C_{1j}})}, \tag{2}$$

where Imp$(\widetilde{E1/C1})$ refers to the fuzzy number Imp (E1/C1).

The final weighted coefficients for the Proportional-Integral-Derivative (PID) gain criteria are computed utilizing the mean values $(\widetilde{w1}, \widetilde{w2}, \ldots, \widetilde{wn})^T$. Eq. (3) is employed to generate the final value of each criterion's weight using the fuzzy EDM ($\widetilde{\text{EDM}}$).

$$\widetilde{w}_J = \left(\left(\sum_{i=1}^{m} \frac{\text{Imp}(\widetilde{E}_{IJ}/C_{IJ})}{\sum_{j=1}^{n} \text{Imp}(\widetilde{E}_{IJ}/C_{IJ})} \right) \Big/ m \right), \text{for } i = 1,2,3,.m \text{ and } j = 1,2,3,.n. \tag{3}$$

In addition, the centroid method is used as a standard defuzzification technique to convert fuzzy weights into crisp values. This method uses a mathematical expression $\frac{(a+b+c)}{3}$ when working with TFNs. For example, if a fuzzy weight of a criterion is (0.50,0.75,0.90), its crisp weight will be:

$$\frac{0.50 + 0.75 + 0.90}{3} = 0.717$$

2.3. Phase three: benchmarking phase

This section explains the process of the CODAS method for ranking based on pre-indicated criteria that are taken from the FWZIC. CODAS method was introduced by [16]. The CODAS method of assessment is based on the Euclidean distance of alternatives' from a negative-ideal point (Abdullah [1]). This distance measure requires an L2-norm indifference space. The distance from a negative-ideal solution is construed as the measure for desirable alternatives, in that longer distances are better. In instances where alternatives cannot be construed as better or worse using Euclidean distance, the options can be evaluated with a Taxicab distance. Hence, the CODAS method typically utilizes both the L2-norm and L1-norm indifference spaces. In this method, assuming there are n alternatives and m criteria, the procedural steps are as follows:

Step A: Construction of the decision matrix (DM). As seen in Eq. (4), this step constructs a decision matrix of (D).

$$D = \left[d_{ij}\right]_{nxm} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1m} \\ d_{21} & d_{22} & \cdots & d_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nm} \end{bmatrix}, \tag{4}$$

where d_{ij} ($d_{ij} \geq 0$) characterizes an alternative's performance value for a criterion ($i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, m\}$).

Step B: Calculation of the normalized decision matrix. To generate the normalized DM, linear normalization of the performance values is utilized in this step, as in Eq. (5). The normalized score will be in a 0–1 range, where the higher score is the better for benefit criteria, while the lower score is the better for cost criteria.

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_i x_{ij}} \text{ if } j \in N_b \\ \dfrac{\min_i x_{ij}}{x_{ij}} \text{ if } j \in N_c \end{cases}, \tag{5}$$

where N_b and N_c are the sets of benefit and cost criteria, respectively.

For instance, if the values of alternatives for a benefit criterion is [10, 20, 5], the normalized scores will be [10/20, 20/20, 5/20] = [0.5, 1, 0.25]. On the other hand, if the criterion is a cost critrion the normalized scores will be [5/10, 5/20, 5/5]= [0.5, 0.25, 1].

Step C: Calculation of the weighted normalized DM. To generate the weighted normalized performance value, Eq. (6) is applied.

$$r_{ij} = w_j n_{ij}, \tag{6}$$

where w_j $\left(0 < w_j < 1\right)$ represents the j^{th} criterion's weight, and $\sum_{j=1}^{m} w_j = 1$.

For example, if the weight of C_2 is 0.3 and a normalized score of 0.8: $r_{ij} = 0.3 * 0.8 = 0.24$.

Step D: Determination of the ideal negative solution. This step is employed to find the worst performance of each criterion. To accomplish this step, Eqs. (7) and (8) are applied.

$$\boldsymbol{NS} = \left[ns_j\right]_{1xm},\ j = 1, \ldots\ldots, m, \tag{7}$$

$$ns_j = \min_i r_{ij}. \tag{8}$$

For example, if the weighted scores for C_2 are [0.24, 0.18, 0.30], then $ns_2 = 0.18$.

Step E: Determination of Euclidean and Taxicab distances. This step involves calculating the distances of alternatives from the ideal negative value, which means that this step measure how far each alternative is from the worst-case scenario, and it is calculated using Eqs. (9) and (10).

$$E_i = \sqrt{\sum_{j=1}^{m} \left(r_{ij} - ns_j\right)^2}, \tag{9}$$

$$T_i = \sum_{j=1}^{m} \left|r_{ij} - ns_j\right|. \tag{10}$$

Step F: Construction of the relative assessment matrix. By utilizing Eqs. (11) and (12), the matrix of the relative assessment is constructed to compare alternatives pairwise.

$$R_a = \left[h_{ik}\right]_{nxn}, \tag{11}$$

$$h_{ik} = \left(E_i - E_k\right) + \left(\psi\left(E_i - E_k\right) \times \left(T_i - T_k\right)\right), \tag{12}$$

where $\psi(E_i - E_k)$ is a threshold function

Table 4
Results of the evaluation decision matrix.

Alternative	Evaluation Criteria				
	C_1	C_2	C_3	C_4	C_5
A_1	1	0	1	1	0
A_2	0	0	1	0	0
A_3	0	0	1	1	0
A_4	1	0	0	0	0
A_5	1	1	1	0	0
A_6	0	1	1	0	0
A_7	0	1	0	1	0
A_8	0	1	0	0	1

$$\psi(x) = \begin{cases} 1 \text{ if } |x| < \tau \\ 0 \text{ if } |x| \geq \tau \end{cases}, \tag{13}$$

and $\tau \in [0.01, 0.05]$ is the threshold parameter, with preferred value (0.02), to employ the Euclidean distance solely. If the difference between the Euclidean distances for two alternatives is less than τ, the Taxicab distance is added to the measure of comparison. For instance, If $E_i = 0.116$, $E_k = 0.100$, $\tau = |E_i - E_k| = 0.016 < 0.02$, then, the Taxicab distance is utilized $T_i = 0.16$, $T_k = 0.12$, and $h_{ik} = (0.116 - 0.100) + (0.16 - 0.12)) = 0.056$.

Step G: Calculation of each alternative's assessment score. This step sums all pairwise comparisons for each alternative utilizing Eq. (13).

$$H_i = \sum_{k=1}^{n} h_{ik}. \tag{14}$$

Step H: Ranking of alternatives. The last step is ranking the alternatives on the basis of the decreasing assessment score values (H_i). The best choice among the alternatives is the alternative with the highest H_i score.

Finaly, the proposed methodology for the entire research can be summarized in two parts. The first part was discussed above with relation to the first two phases, while the last part is discussed after the results for the evaluation. All these steps can be summarized based on the following step by step flow.

1. Define criteria (C_1, C_2, …, C_5) and alternatives (A_1, A_2, …, A_8) based on literature review.
2. Collect expert evaluations using a 5-point Likert scale (Table 2), converting linguistic terms (e.g., "Very Important") to numerical scores (1–5).
3. Build the Expert Decision Matrix (EDM): Rows = Experts (ET_1, ET_2, ET_3), Columns = Criteria (C_1–C_5), Cells = Numerical scores.
4. Convert numerical scores to Triangular Fuzzy Numbers (TFNs) using Table 4 (e.g., "Very Important" → (0.75, 0.90, 1.00)).
5. Construct the Fuzzy Expert Decision Matrix (FEDM) by replacing EDM entries with TFNs.
6. Calculate fuzzy weights ($\widetilde{w}_j$) for each criterion:
   a. Sum TFNs across criteria for each expert:

$$\widetilde{\text{Sum}}_i = \sum \left(\widetilde{\text{Imp}}(\text{ET}_i|C_1),\ \widetilde{\text{Imp}}(\text{ET}_i|C_2),\ \ldots, \widetilde{\text{Imp}}(\text{ET}_i|C_5)\right).$$

   b. Normalize each expert's evaluations dividing by the total sum of the criteria:

Table 5
EDM results.

Expert/Criteria	C_1	C_2	C_3	C_4	C_5
Expert 1	5	2	4	4	1
Expert 2	5	1	3	4	2
Expert 3	5	3	4	5	2

Table 6
TFN-EDM.

Criteria	C_1	C_2	C_3	C_4	C_5
Expert 1	(0.75,0.90,1.00)	(0.10,0.30,0.50)	(0.50,0.75,0.90)	(0.50,0.75,0.90)	(0.00,0.10,0.30)
Expert 2	(0.75,0.90,1.00)	(0.00,0.10,0.30)	(0.30,0.50,0.75)	(0.50,0.75,0.90)	(0.10,0.30,0.50)
Expert 3	(0.75,0.90,1.00)	(0.30,0.50,0.75)	(0.50,0.75,0.90)	(0.75,0.90,1.00)	(0.10,0.30,0.50)

Table 7
Final weights of the criteria.

Criteria	C_1	C_2	C_3	C_4	C_5
Final weight	0.298	0.121	0.225	0.263	0.093

$$\widetilde{Imp}(ET_i|C_j)_{nor} = \widetilde{Imp}(ET_i|C_j)/\widetilde{Sum}_i$$

c. $\widetilde{W}_j = \sum\left(\widetilde{\text{Imp}}(\text{ET}_1|C_j)_{nor}, \widetilde{\text{Imp}}(\text{ET}_2|C_j)_{nor}, \widetilde{\text{Imp}}(\text{ET}_3|C_j)_{nor}\right)/3.$

7. Defuzzify TFN weights using centroid method: $W_j = (a+b+c)/3$.
8. Normalize crisp weights to ensure $\sum w_j = 1,\ w_j = W_j / \sum W_j$
9. Normalize the decision matrix (D):
   For each criterion C_j:
   If C_j is a benefit criterion (higher = better):

$$n_{ij} = \frac{x_{ij}}{\max_i x_{ij}}$$

If C_j is a cost criterion (lower = better):

$$n_{ij} = \frac{\min_i x_{ij}}{x_{ij}}$$

10. Apply criteria weights to the normalized matrix: $r_{ij} = w_j n_{ij}$
11. Determine the negative-ideal solution for each criterion: $ns_j = \min(r_{1j}, r_{2j}, \ldots, r_{8j})$.
12. Calculate Euclidean (E_i) and Taxicab (T_i) distances from NS:

$$E_i = \sqrt{\sum_{j=1}^{m}(r_{ij} - ns_j)^2}$$

$$T_i = \sum_{j=1}^{m}|r_{ij} - ns_j|$$

13. Build the relative assessment matrix $H = [h_{ik}]$
    For each pair of alternatives (A_i, A_k):

$$\text{If } (E_i - E_k) \geq 0.02$$

$$h_{ik} = (E_i - E_k)$$

$$\text{If } (E_i - E_k) < 0.02$$

$$h_{ik} = (E_i - E_k) + (T_i - T_k),$$

14. Calculate assessment $H_i = \sum_{k=1}^{n} h_{ik}$.
15. Rank alternatives in descending order of H_i.
16. Validate robustness via sensitivity analysis:
    a. Perturb criteria weights (e.g., swap highest/lowest weights).
    b. *Re*-run Steps 9–15 and compare ranks.

3. Results and discussion

This section displays the outcomes of the proposed evaluation and benchmarking framework for the area of AI energy management.

3.1. Results of DM evaluation

In this section, the results of the evaluation of DMs are presented. The evaluation results are shown in Table 4. The DM of this study includes 8 alternatives and 5 criteria. For each criterion, the evaluation score of each alternative is represented by a numerical value.

3.2. Weighting results

In this section, the results of the weights of the evaluation criteria utilizing the FWZIC are provided following the steps provided above. The first step, as mentioned above, was identifying the evaluation criteria (***C₁, C₂, C₃, C₄***, and ***C₅***); then, the opinions of the three experts were collected. These opinions were converted into their equivalent numerical values, as shown in Table 4.

The values in Table 5 indicate the importance of each criterion in accordance with the opinion of the expert.

The next step was converting the EDM into TFN-EDM, as shown in Table 6. In this process, crisp values are converted into equivalent fuzzy numbers. Then, Eqs. (2) and (3) are applied to get the final fuzzy weights

Table 9
Results of the euclidean and taxicab distances.

Alternative	Ei	Ti
A_1	0.4568062	0.7860991
A_2	0.2250567	0.2250567
A_3	0.3459016	0.4877303
A_4	0.2983689	0.2983689
A_5	0.392839	0.6444545
A_6	0.2555357	0.3460856
A_7	0.2892152	0.3837026
A_8	0.1525556	0.2139009

Table 8
Weighted DM.

Alternative	C_1	C_2	C_3	C_4	C_5
A_1	0.298368853	0	0.225056672	0.262673615	0
A_2	0	0	0.225056672	0	0
A_3	0	0	0.225056672	0.262673615	0
A_4	0.298368853	0	0	0	0
A_5	0.298368853	0.121028954	0.225056672	0	0
A_6	0	0.121028954	0.225056672	0	0
A_7	0	0.121028954	0	0.262673615	0
A_8	0	0.121028954	0	0	0.09287191

of the criteria.

The final step involves extracting the criteria's final weight through the process of defuzzification. The weighting results of the five evaluation criteria, as highlighted in Table 7, are based on TFN-FWZIC.

According to the results of criteria weighting, the most significant factor is the criterion with the highest number. The most significant weight criterion is C_1 (robustness), with a value of *0.298*, followed by C_4 (intelligent design), with a value of ***0.263***. The third weight belongs to C_3 (computational burden), with a value of *0.225*, followed by C_2 (feedback response), with a value of *0.121*. The lowest significance value was observed for C5 (online monitoring), with a value of ***0.093***.

3.3. Benchmarking using CODAS

In this section, the findings of utilizing CODAS are presented to compare energy management ML models for benchmarking alternatives. The weighted normalized decision matrix is generated based on the final criteria weights, as presented in Table 8.

Then, the Euclidean (E_i) and taxicab (T_i) distances are generated utilizing Eqs. (9) and (10) after determining the negative ideal value, as highlighted in Table 9.

Then, the relative assessment matrix (RA) is built utilizing Eqs. (11) and (12) with the aid of Eq. (13). The final step is the calculation of the alternatives' assessment scores (H), as indicated in Table 10.

As seen in Table 11, the highest score of assessment reflects the best option of performance, which belongs to A1 with a score of 1.237865, followed by A5 with a score of 0.724202. Conversely, A8 obtained the minimum assessment score, followed by A2, with the remaining options falling in varying positions between the two.

In summary, although these results present a structured evaluation of ML models based on expert-defined criteria, we recognize that real-world implementation also demands attention to factors such as run-time efficiency and resource consumption. The computational demand of the adopted MCDM methods (FWZIC—CODAS integrated model) remains manageable, involving operations proportional to the product of the number of criteria and alternatives—suggesting practical feasibility even with larger datasets. Since the framework primarily relies on straightforward matrix operations, it can be seamlessly coded and embedded into energy decision support systems using tools like Python, R, or MATLAB. Nonetheless, a thorough assessment of system integration overhead, processing latency, and scalability with live data sources is outside the present scope. Future studies are planned to explore these operational dimensions in greater detail.

4. Sensitivity analysis

In the sensitivity analysis, the impact of the highest criteria weight is estimated in terms of its relative impact on the results of the alternative benchmarking. In previous literature, sensitivity analysis was used to assess how changes in the weights of the criteria affect the sensitivity measurement [3,4]. Utilizing FWZIC weights to evaluate attributes in ML energy management systems allows for sensitivity analysis to determine the effectiveness and impact that strategy can have on the overall ranking of alternatives. It provides for improved strength and consistency of decisions. One approach for sensitivity analysis involves the distribution of the weights assigned to each of the criteria to see how much the outcome of the decision is affected resulting from changes in important levels. In this case, the criterion with the highest weight is systematically reassigned to each of the other criteria, one at a time, for different scenarios, to assess the effects of assigning different criteria as the most important. A similar process is applied in the opposite direction with the criterion with the lowest weight, for different scenarios. The methodology is typically used in sensitivity analysis associated with decision-making, generally related to MCDM methodologies. This approach affords decision-makers an opportunity to analyze how responsive decisions are where importance weights were applied to evaluation attributes by how responsive those were when applied to one another. Also, it allows decision-makers to validate the robustness of the proposed framework. Decision-makers are able to make more informed decisions and assess the weight assigned to multiple scenarios based on one actual weight circumstance that is believed to be the most important, otherwise also including weights given minimum weight on higher extent, or simply recognized cognizance given for the criterion. Overall, decision-makers that weigh that process can account for multiple scenarios in which weightings may be attributed, provide understanding of relative dependency on criterion and thereby varying the significance of those decision-making advantages were that uncertainty, biases, weight, weight shift, and/or study beyond completed evaluations systems appropriate, thereby accurately evaluating possible drawbacks. Table 12 illustrates the weights of the criteria for all of the previously discussed scenarios to demonstrate the gradual shift in weights in each scenario as workaround on sensitive analysis provided both a descriptive and databank into weight processes in energy.

To assess the impact of the weights on ML energy management benchmarking, the weights extracted from Table 12 are applied. Then, the rank for each scenario is extracted using the CODAS method and compared with the original results, as highlighted in Table 13.

To visualize the variations in ranks, Fig. 3 is illustrated. On the basis of Table 12 and Fig. 3, the results show some variability for certain alternatives but remain relatively stable for others across different scenarios.

"A1 : ANN" maintained the highest rank in most of the scenarios (5/7) except for the first and seventh scenarios. In the first scenario, when the weight of the second criterion "C_2 : feedback response" increased and "C_1 : robustness" decreased, A1 retreated to the third position and "A5: RF" advanced to the first position, indicating the premium performance

Table 11
Alternatives scores and ranks.

Alternative	H	Rank
A_1	1.237865	1
A_2	−0.61594	7
A_3	0.352964	3
A_4	−0.11794	5
A_5	0.724202	2
A_6	−0.37216	6
A_7	−0.01394	4
A_8	−1.19505	8

Table 10
Relative assessment matrix.

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	0	0.231725	0.110613	0.158725	0.064208	0.201253	0.167226	0.304115
A_2	−0.23173	0	−0.12111	−0.073	−0.16752	−0.03047	−0.0645	0.072389
A_3	−0.11061	0.121113	0	0.048113	−0.0464	0.090641	0.056613	0.193502
A_4	−0.15873	0.073	−0.04811	0	−0.09452	0.042528	−0.0775	0.145389
A_5	−0.06421	0.167518	0.046405	0.094518	0	0.137045	0.103018	0.239907
A_6	−0.20125	0.030472	−0.09064	−0.04253	−0.13705	0	−0.03403	0.102861
A_7	−0.16723	0.0645	−0.05661	0.0775	−0.10302	0.034027	0	0.136889
A_8	−0.30411	−0.07239	−0.1935	−0.14539	−0.23991	−0.10286	−0.13689	0

Table 12
Criteria weights of the different scenarios.

	C_1	C_2	C_3	C_4	C_5
Original weight	0.298	0.121	0.225	0.263	0.093
S_1	0.121	0.298	0.225	0.263	0.093
S_2	0.225	0.121	0.298	0.263	0.093
S_3	0.263	0.121	0.225	0.298	0.093
S_4	0.093	0.121	0.225	0.263	0.298
S_5	0.298	0.093	0.225	0.263	0.121
S_6	0.298	0.121	0.093	0.263	0.225
S_7	0.298	0.121	0.225	0.093	0.263

Table 13
Alternative weights in each scenario.

Alternatives	Original	S_1	S_2	S_3	S_4	S_5	S_6	S_7
A_1	1	3	1	1	1	1	1	2
A_2	7	7	6	7	7	7	8	7
A_3	3	5	3	3	2	3	4	6
A_4	5	8	7	6	8	4	5	4
A_5	2	1	2	2	4	2	2	1
A_6	6	4	4	5	6	6	7	5
A_7	4	2	5	4	5	5	3	8
A_8	8	6	8	8	3	8	6	3

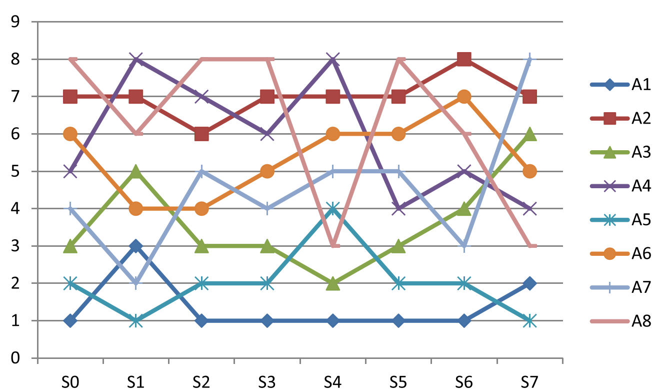

Fig. 3. Benchmarking results for each scenario.

of A1 regarding "C_1 : robustness" and A5 regarding "C_2 : feedback response". In the seventh scenario, where "C_2 : intelligent design" has the minimum weight, A1 retreated to the second position, indicating its superiority for this criterion. A5 maintained the second place in most scenarios (4/7) except for the first, fourth, and seventh scenarios. It attained the first position when the criteria "C_2 : feedback response" and "C_2 : online monitoring" increased, and retarded to the fourth position when "C_2 : robustness" decreased.

On the other hand, "A8:IoT and RNN" maintained the lowest rank in three scenarios (3/7). It advanced to the sixth position in the first and sixth scenarios, and jumped to third in the fourth and seventh scenario when the criteria "C_2 : feedback response" and "C_2 : online monitoring" increased. Furthermore, "A2:SVM" maintained the second-lowest rank in five scenarios (5/7). Little advancement is achieved to the sixth position when the weight of "C_3 : computational burden" increased, and it retarded to the last position when C_3 decreased. Hence, the criterion "C_3 : computational burden" is the only criterion that affects A2.

As for the middle-ranked alternatives, "A3:ELM" third place, "A7: hybrid ML and RL" fourth place, "A4:CNN and RNN" fifth place, and "A6: RL" sixth place, they interchanged their positions except for some remarkable instances. "A3:ELM" achieved the second place when "C_5: online monitoring" increased. Likewise, "A7:hybrid ML and RL" moved to the second place with the increment of "C_2:feedback response". On the contrary, "A4:CNN and RNN" retarded to the last position when "C_1: Robustness" decreased.

From the previous, the sensitivity analysis was able to portray the influence of the assessment criteria on the rank of the alternatives and on the selection of the most effective ML models. Despite the weight variations, the proposed framework emphasized on the selection of "A1: ANN" and "A5:RF" as the best models.

5. Comparative analysis

This section is dedicated to comparing the results obtained by the proposed framework with the results of other methods. Firstly, the relative importance of the criteria is re-evaluated. Two subjective weighting techniques are applied, Stepwise Weighted Assessment Ratio Analysis (SWARA) and direct aggregation of experts' evaluations. These methods were chosen due to their ability to handle the current form of collected data. From Table 14, despite the slight difference in the weights obtained, which is common for different weighting methods, the relative importance of the criteria remains unchanged.

The results in Table 15 are illustrated in Fig. 4.

Secondly, the results of the CODAS method for prioritizing ML models are compared with the results of four well-known methods successfully applied in diverse applications. Three of these methods are distance-based methods, i.e. reference point techniques, similar to CODAS. The main difference is in the reference point. While CODAS uses the negative ideal value, VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) employs the positive ideal value. Meanwhile, TOPSIS utilizes both the negative and positive ideal values. The Evaluation based on the Distance from Average Solution (EDAS) method uses the distances of the alternatives from the average values of the attributes for the evaluation of the alternatives. For diversity, the Weighted Sum Method (WSM) is also used in comparison as a different approach, being based on aggregation operators. Table 15 summarizes the results of the four methods. When VIKOR is applied, the weight of the maximum group utility strategy "γ" is set to half.

Applying Spearman's rank correlation, the correlation between CODAS's rank and that of TOPSIS, VIKOR and the WSM was 97.2 %. The correlation between CODAS's rank and that of EDAS was 80.9 %. Hence, there is a strong positive correlation between different ranks. From Table 15, the applied methods agreed on "A1:ANN" as the most effective model, followed by "A5:RF" which occupied the second position in three methods. Different ranks are shown in Fig. 5.

6. Conclusion

In conclusion, this study advances energy management research by illustrating a comprehensive MCDM model that implements FWZIC and CODAS to alleviate the issue of selecting better ML models for energy management systems. Using a specified set of criteria driven by aspects of resilience, eight alternative ML models were assessed on the following five categories: robustness, feedback response, computational burden, intelligent design, and monitoring online. The primary intention of the MCDM framework, conducted between the realms of ML theoretical advances and practical deployment, is to interpret the results as responsive to questions about energy demand. Results show that

Table 14
Results of criteria comparison.

Method	FWZIC		SWARA		Direct Aggregation	
Criteria	Score	Relative Importance	Score	Relative Importance	Score	Relative Importance
C_1	0.298	1	0.259	1	0.308	1
C_2	0.121	4	0.156	4	0.110	4
C_3	0.225	3	0.208	3	0.227	3
C_4	0.263	2	0.233	2	0.269	2
C_5	0.093	5	0.145	5	0.085	5

Table 15
Results of rank comparison.

Method	CODAS	TOPSIS		VIKOR (γ = 0.5)		EDAS		WSM	
Alternatives		Score	Rank	Score	Rank			Score	Rank
A_1	1	0.749647	1	0	1	0.863868	1	0.786099	1
A_2	7	0.345792	7	0.990385	7	0.426952	5	0.225057	7
A_3	3	0.507925	3	0.76049	3	0.63178	2	0.48773	3
A_4	5	0.441101	4	0.827703	4	0.595955	4	0.298369	6
A_5	2	0.585063	2	0.525256	2	0.62525	3	0.644454	2
A_6	6	0.384982	6	0.884615	6	0.203596	8	0.346086	5
A_7	4	0.428904	5	0.851399	5	0.369513	6	0.383703	4
A_8	8	0.250353	8	1	8	0.360748	7	0.213901	8

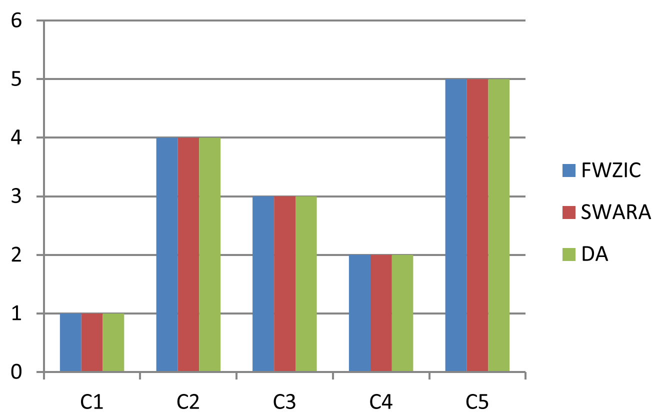

Fig. 4. Comparison of the relative importance of the criteria.

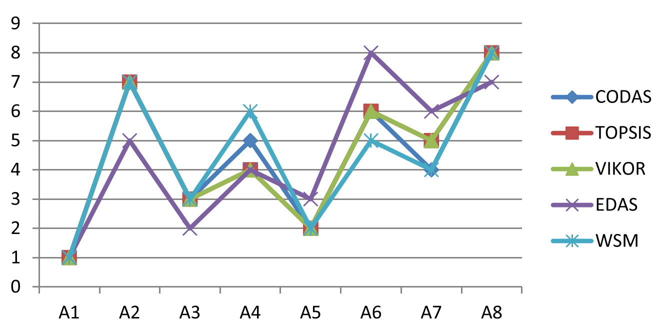

Fig. 5. Comparison of the different ranks.

robustness accounted for the largest weight, illustrating the basis for reducing uncertainty in complex and dynamic energy scenarios. Also, the proposed method assists in providing practical guidance for implementing AI solutions in various energy management applications. Amongst the eight assessed alternatives, hybrid ANNs achieved the highest designation model and performed in the top rank for five of the seven sensitivity analysis scenarios, demonstrating the analysis provides a stable solution when criteria weights fluctuate.

The merging of FWZIC and CODAS constitutes a methodological improvement over traditional MCDM methodologies. The reduction of variations in rankings through FWZIC, in terms of reducing consequences of inconsistency with expert developed weights, along with the distance metric of dual distance through CODAS resulted in lower rank variability relative to TOPSIS ranking. Connective pairings of roughness, uncertainty, and/or conflicts of criteria dimensions models will ensue providing reliable information for potential uncertainty associated with an energy systems MCDM challenge. The decision-making utility and significance are further associated with stakeholders' communities to the corresponding purpose in prioritizing models under evaluation, providing an accessible means for policymakers or local industry additional transparency to address issues in balancing accuracy, cost, and versatility.

This study expands the body of knowledge on energy management for the implementation of FWZIC with CODAS for MCDM, however, several limitations should be considered. The framework was validated using datasets from a previous study. Hence, future work can expand the dataset and test the framework on more ML-based solutions to test applicability and potential operational scalability and interoperability with existing hardware network infrastructure focusing on various real-time energy management AI solutions. Also, the exclusion of ethical aspects, such as addressing bias in machine learning training datasets or equitable access to AI-based applications, further emphasizes the urgency of interdisciplinary research that links technical and societal aspects. Future work should consider the feasibility of incorporating ethical measures into the MCDM process to make certain that AI deployments are ethical, fair, and accessible. Moreover, three experts participated in this study for criteria evaluation, which is the minimum number of experts accepted. Future work should expand the number of experts to be higher. While the framework in this study is robust under perturbations of the weights, there may be opportunities to advance uncertainty modelling using other fuzzy environments such as interval type-2 fuzzy sets and Pythagorean fuzzy sets. This would potentially allow for more flexibility to address ambiguities in judgements made by experts as well as the dynamics of effects produced by systems. By addressing these limitations, a next version of this work would be refinements to the tension between theoretical possibilities and practical applications, while also developing ML models that perform and are resilient in energy transitions globally. Finally, future work should also investigate the computational load and cost-efficiency of deploying this framework within live energy infrastructure, including API-based integration and scaling with IoT sensor streams.

CRediT authorship contribution statement

Salem Garfan: Writing – original draft, Software. **A.H. Alamoodi:** Writing – review & editing, Visualization. **Suliana Sulaiman:** Validation, Supervision. **O.S. Albahri:** Project administration, Formal analysis. **A.S. Albahri:** Investigation, Data curation, Conceptualization. **Iman Mohamad Sharaf:** Resources, Methodology.

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.

Data availability

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

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