Energy Policy 182 (2023) 113775

Contents lists available at ScienceDirect

Energy Policy

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

Multi-perspective evaluation of integrated active cooling systems using fuzzy decision making model

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ARTICLE INFO

Keywords:
Integrated active cooling systems
Household energy consumption
Climate change
2-Tuple linguistic pythagorean fuzzy sets
FWZIC
MABAC

ABSTRACT

As global median temperatures continue to rise, the demand for active cooling systems (ACs) is increasing. These systems are particularly prevalent in developed countries for maintaining comfort during hot weather. Various ACs technologies are available, and assessing their performance in multi-perspective settings is necessary to determine the best option for intended usage. This requires an evaluation platform for assessment. This paper presents a novel multi-criteria decision-making (MCDM) model based on a new integrated 2-tuple linguistic Pythagorean fuzzy-weighted zero-inconsistency (2 TLP-FWZIC) and modified 2-tuple linguistic Pythagorean fuzzy multi-attributive border approximation area comparison (2TLPF-MABAC). The former is used to determine the importance of assessment criteria, while the latter is employed for selecting the optimal ACs using the obtained weights. The first-level weighting results reveal that performance criteria were predominantly favored for assessment, with 'energy performance' acquiring the most significant weight (*0.2487*) among all performance criteria. In terms of ACs selection results, among the 20 tested and assessed systems, the 'geothermal borehole electricity-based ACs' obtained the highest score value (*0.1296*), while the 'window packaged electricity-based ACs' had the lowest score (-*0.0515*). The robustness of the results was confirmed through sensitivity analysis.

1. Introduction

Household energy consumption is a significant contributor to climate change, and cooling systems play a key role (Jakučionytė-Skodienė et al., 2022). As global median temperatures continue to rise, the demand for active cooling systems (*ACs*) is increasing. Cooling systems, particularly prevalent in developed countries where they are considered essential for maintaining comfort during hot weather (Malik et al., 2022), primarily rely on electricity for operation. However, the generation of electricity often involves the burning of fossil fuels such as coal, natural gas, and oil. When these fossil fuels are burned, they release greenhouse gases that contribute to global warming (Shamoon et al., 2022). Consequently, the energy used by cooling systems indirectly contributes to climate change through the release of these gases during electricity generation. Therefore, the energy used by ACs indirectly contributes to greenhouse gas emissions and climate change, as it is derived from sources that release greenhouse gases into the atmosphere. ACs are one of the greatest energy consumers in buildings because they are essential for occupant well-being. Therefore, improving the performance of conventional Heating, Ventilation, and Air-Conditioning

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https://doi.org/10.1016/j.enpol.2023.113775
Received 11 May 2023; Received in revised form 13 June 2023; Accepted 11 August 2023
Available online 18 August 2023

(*HVAC*) systems presents opportunities for substantial energy savings (Taheri et al., 2022). Currently, various cooling systems that use either electricity or thermal energy are available on the market, designed to work in different climates. Although there are a variety of commercially available ACs, vapour compression (*VC*) air-conditioning systems are the most prevalent in residential buildings worldwide (Al-Yasiri et al., 2022). Thermal energy-driven cooling systems have been on the market for decades, relying on the availability of a substantial quantity of waste heat to power the systems. Thermal energy-driven cooling systems are more closely linked with renewable energy sources (Elnagar et al., 2023). Evaporative cooling, known as a 'swamp cooler' or 'wet air cooler' is another strategy, particularly popular in arid climates, which takes advantage of relative humidity differentials consumes about one-eighth of the electricity of refrigerated air (Cuce and Riffat, 2016; Reference, 2004), but is not of practical use in every locale.

The studies reviewed various cooling technologies, some focusing on VC systems alone (Zhang et al., 2021), while others centring on thermal energy-driven cooling systems (Gado et al., 2021). Zhang et al. (Zhang et al., 2021) conducted a thorough qualitative analysis of cooling techniques, focusing on their efficacy during heatwaves and power outages. While the study investigated some compression refrigeration technologies, it did not focus on the integration of different types of compression refrigeration systems with secondary systems. Pezzutto et al. (Pezzutto et al., 2022a) investigated alternative cooling technologies utilising conventional VC systems and discovered that no technologies are presently prepared to compete with VC systems on the EU market. Hughes et al. (Hughes et al., 2011) examined sustainable active and passive cooling methods in buildings and showed that under certain external conditions, passive cooling can reduce indoor temperatures as well as ACs. Oropeza-Perez and Østergaard (2018) studied three active and ten passive cooling technologies and developed a decision-making tool for selecting the optimum technology for different buildings based on climate, building type, and the cooling technology's initial cost. The strategy neglected occupant behaviour, technology integration, and cooling technology performance under severe events like heatwaves and power outages. Moreover, Kojok et al. (Kojok et al., 2016) outlined the typical standalone cooling technologies utilized in hybrid building cooling. Elnagar et al. (Elnagar et al., 2023) highlights the need for a comprehensive review of cooling systems, including those driven by electricity and thermal energy, within the HVAC research field. The study notes a lack of qualitative assessment that considers important factors such as energy performance, system flexibility, resilience to extreme weather conditions, building type, and technology readiness level (*TRL*). This study evaluated the performance of cooling systems based on three technical features: reversibility, recovery, and passivity, and compared different systems using the five assessment criteria mentioned above. However, there is still a significant gap in the current literature. Despite numerous studies reviewing different types of cooling systems, there is no exclusive study that has presented an integrated solution to evaluate and select the optimum ACs within the HVAC research field. This gap in the literature underscores the need for a comprehensive study that addresses this issue. Such a study would need to take into account a number of parameters, including energy performance, the flexibility of integration with secondary systems and renewable energies, climate resilience to extreme events like heatwaves and power disruptions, building types, and TRL. Moreover, the study should develop a new decision-making methodology that can evaluate and compare different ACs, identify their strengths and weaknesses, and select the optimal solution based on the specific requirements of each building. Such a tool would be a valuable contribution to the HVAC research field and could help to reduce energy consumption and promote sustainable building practices.

To fill the research gap, several technical challenges must be addressed. Firstly, decision-making involves multiple evaluation criteria, each with its sub-criteria and perspective, such as technical and performance criteria. The decision-making process is complex because several factors cannot be compared on a single scale. Secondly, the evaluation criteria are interrelated, and changes in one criterion may impact others, leading to conflicting criteria. Thirdly, in the evaluation of ACs, data variation occurs when some alternatives perform better than others on one criterion, while different alternatives may perform better on other criteria. Fourthly, the decision-making relies on multiple evaluation criteria. However, experts' subjective preferences and their varying importance levels for each criterion make it a challenging task to make a decision. Based on the technical challenges mentioned earlier, the process of selecting appropriate ACs within the HVAC research field involves a complex multi-criteria decision-making (*MCDM*) process that needs to be addressed in this study. This process requires a comprehensive evaluation of the ACs from multiple perspectives, taking into account various technical and performance criteria. The decision-making process needs to consider the interrelatedness of the evaluation criteria and the potential conflicts that may arise. Moreover, the varying importance levels of the criteria, which are subjective and depend on expert preferences, add to the complexity of the decision-making process. Therefore, this study aims to solve the complex multi-criteria decision-making problem associated with the selection of ACs in the HVAC research field. The study will develop a systematic approach that incorporates various evaluation criteria and provides an approach for evaluating and selecting the most suitable ACs. The aims of this study are presented as follows.

1. A multi-perspective decision matrix was formulated that takes into account technical and performance criteria and an alternative list of ACs.
2. A new version of fuzzy-weighted zero-inconsistency (*FWZIC*) was developed, called 2-tuple linguistic Pythagorean fuzzy-weighted zero-inconsistency (2TLP-FWZIC) which assigns coefficient weights to the technical and performance criteria of ACs.
3. A modified version of multi-attributive border approximation area comparison (*MABAC*) was developed, called the 2-tuple linguistic Pythagorean fuzzy multi-attributive border approximation area comparison (*2TLPF-MABAC*) to rank and select the most suitable ACs.
4. The proposed MCDM approach was evaluated using sensitivity analysis, which involved testing the approach using different sets and scenarios of ACs criteria weights.

The remainder of this paper's sections are organised as follows. Section 2 discusses the related scholarly literature on MCDM. In Section 3, the methodology of the proposed MCDM model is formulated. Section 4 describes the details of ACs to be used in the multi-perspective decision matrix. The evaluation and selection results are discussed in Section 5. Section 6 discusses the study's implications. Finally, Section 7 concludes the study.

2. Related works

MCDM is a field of study that deals with making decisions when there are multiple criteria to consider. In traditional decision-making approaches, a single criterion is used to evaluate the options available and select the best one (Alamleh et al., 2022). However, in many real-world situations, multiple criteria need to be taken into account, and these criteria may be conflicting or incommensurable. MCDM techniques provide a systematic approach to dealing with these complex decision-making scenarios by allowing decision-makers to consider multiple criteria and weigh them according to their relative importance. These techniques can help to identify the most suitable option based on the preferences of the decision-maker and the criteria used to evaluate the alternatives (Alsalem et al., 2021). MCDM has numerous applications in many different fields, including engineering (Ismael, 2023), energy (Sotiropoulou and Vavatsikos, 2021), business economics and operations research (Mohammed et al., 2019), environmental management (Akbari et al., 2021), and healthcare (Alsalem et al., 2022). The field of MCDM is constantly evolving, with new techniques and approaches being developed to deal with increasingly complex decision-making scenarios.

Understanding the varying development goals and purposes behind MCDM methods is crucial due to their variety. Different MCDM techniques serve different functions; some are utilized for selecting and ranking decision options while others are employed to assign weight and importance values to decision criteria. Several robust MCDM methods have been introduced over time, each addressing unique challenges in MCDM. MABAC is a well-known MCDM ranking method (Pamučar and Ćirović, 2015). MABAC boasts several potential advantages. It's a user-friendly MCDM method that does not require significant technical expertise, making it accessible to a wider audience. Moreover, it provides a clear ranking of alternatives based on their overall performance against the given criteria. MABAC is capable of handling imprecise or vague data, making it a suitable method for decision-making problems that involve uncertain information. MABAC can handle large datasets with numerous alternatives and evaluation criteria, which is a significant advantage in complex decision-making scenarios. In addition, it allows for the incorporation of indifference thresholds, enabling decision-makers to express their preferences for certain criteria and alternatives. Moreover, it provides a visual representation of the decision problem, making it easier for decision-makers to comprehend the results and the decision-making process (Yu et al., 2017).

However, to implement the MABAC method using orthopair fuzzy sets, i.e. sets with two contradicting parameters, the distance measure from the border approximation area (BAA) is a conundrum, as follows. Firstly, the principle of the MABAC is based on measuring the distance from the BAA, which is simply the difference between the weighted rating of an alternative and the BAA. If the distance is a positive value, the alternative belongs to the upper approximation area (UAA); if the distance has a "zero" value the alternative belongs to the BAA; if the distance is negative, the alternative belongs to the lower approximation area (LAA). The distance formulas utilized always give non-negative values. Consequently, distance measures fail to classify the alternatives regarding their position from the BAA. To overcome this problem, two approaches are adopted in the previous research. The first approach depends on defuzzification before computing the distance. However, score functions have a limitation; equal scores might be obtained for different orthopair fuzzy sets leading to the loss of information which might affect the validity of the results. The second approach applies the distance measures in conjunction with the score function to avoid information loss. If the score of an alternative is higher than that of the BAA then it belongs to the UAA and the computed distance is given a positive value. On the other hand, if the score of an alternative is lower than that of the BAA then it belongs to the LAA, and the distance is given a negative value. Secondly, none of the proposed approaches tackled the main drawback of distance formulas. The difference in the "support for" represented by the membership degree (*MD*) and the "support against" represented by the non-membership degree (*NMD*) are equally treated although these differences have dissimilar effects. An increase in the "support for" is an advantage. On the contrary, an increase in the "support against" is a disadvantage. For this, the difference in each grade should be handled as a separate entity. Therefore, a new approach is proposed to implement the MABAC method utilising the 2-tuple linguistic Pythagorean fuzzy sets (*2TLPFSs*) in which the distance measure itself is also represented by a 2TLPFS to handle the present conflict.

Secondly, another significant limitation of MABAC lies in its inability to provide weightings for the evaluation criteria, which can impede its ability to provide comprehensive decision support. Consequently, the integration of another MCDM method that can assign weightings to the evaluation criteria is necessary to compensate for this drawback and enhance the overall effectiveness of the decision-making process. By properly assigning weights to the evaluation criteria, FWZIC can effectively address the limitation of MABAC in this regard, thus enhancing the overall quality of the decision-making process. FWZIC is a decision-making method developed by Mohammed et al. (Mohammed et al., 2021) to capture and reflect decision-makers accumulated knowledge and subjective opinions. This method is particularly useful in mitigating inconsistency problems that arise from the subjective nature of determining the relative significance and importance of different evaluation criteria using a pairwise comparison approach. As the number of criteria increases, the inconsistency rate can escalate, potentially affecting the decision outcomes (Paramanik et al., 2022). While several extensions of FWZIC have been developed to take advantage of different fuzzy environments (Al-Samarraay et al., 2022; Krishnan et al., 2021; Albahri et al., 2022), there is still a need to develop an extension that incorporates the comprehensive advantages of the 2-tuple linguistic model (2 TLM) with fuzzy set applications. The 2 TLM is a mathematical model that uses two numerical values to represent linguistic terms and concepts (Zhang et al., 2022). This approach offers several advantages, including the ability to capture imprecision and uncertainty, which can lead to more accurate analysis and decision-making. The 2 TLM is also highly adaptable, and able to represent a broad range of linguistic concepts and terms, including fuzzy sets and linguistic rules. Furthermore, it can help overcome the limitations of traditional fuzzy sets by allowing for more nuanced and realistic representations of real-world situations (Akram et al., 2023a). Overall, the 2-tuple linguistic model is a versatile tool with potential applications in various fuzzy MCDM processes.

After careful consideration of the points discussed above, it is clear that there is a need to develop a modified version of the 2 TLPF-MABAC method for use in evaluating ACs. To ensure the accuracy and reliability of the evaluation process, the modified 2 TLPF-MABAC method should be integrated with the 2 TLP-FWZIC method, which is a powerful tool for handling uncertainty and imprecision in decision-making. By using the 2 TLP-FWZIC method to provide precise weight coefficients for the evaluating criteria of ACs, the evaluation process can be made more accurate and reliable. In conclusion, the development of a modified version of the 2 TLPF-MABAC method for use in evaluating ACs, integrated with the 2 TLP-FWZIC method, is crucial for ensuring the accuracy and reliability of the evaluation process. This approach has the potential to improve decision-making in the evaluation of ACs and can be applied in a variety of fields.

3. Methodology

This section describes the integrated MCDM approach used for the multi-perspective evaluation of integrated ACs.

3.1. Preliminaries

The 2TLPFS is a recently developed, robust fuzzy set that integrates the merits of the 2 TLM with Pythagorean fuzzy sets (PFSs) to solve complex MCDM problems. The 2TLPFSs and their basic concepts and operations are described as follows.

Definition 2.1. (Akram et al., 2022). A linguistic term set (LTS) denoted as $\boldsymbol{L} = \{l_{0,}l_1, \ldots, l_K\}$ is a set that has an odd cardinality, where K is an even number. Each term of the set symbolizes a possible linguistic term for a linguistic variable, e.g. $\boldsymbol{L} = \{l_0 = bad, l_1 = fair, l_2 = good\}$.

When the indices of some labels in $\boldsymbol{L}$ are aggregated by a symbolic method, the result is $\beta \in [0, \mathrm{K}]$ and $\beta \notin \{0, 1, \ldots, \mathrm{K}\}$. Let the integer value $k = round\,(\beta)$, and $k \in \{0, 1, \ldots, \mathrm{K}\}$, then the value $\kappa = \beta - k$ that satisfies $\kappa \in [-0.5, 0.5)$ is called a symbolic translation. From the previous, a symbolic translation is defined as follows.

Definition 2.2. (Herrera and Martínez, 2000). A symbolic translation (κ) of an LT is the "difference in information" between the result of the symbolic aggregation (β) and the index of the closest linguistic term in $\boldsymbol{L}$ to β, and its value lies in the semi-closed interval $[-0.5, 0.5)$.

Definition 2.3. (Herrera and Martínez, 2000). The linguistic information can be defined by the 2-tuple (l_k, κ), $l_k \in \boldsymbol{L}$ and $\kappa \in [-0.5, 0.5)$, where l_k expresses the linguistic label center of the information, and κ expresses the numerical value of the translation to the closest index (k) from the actual result (β) in an LTS (L).

Definition 2.4. (Herrera and Martínez, 2000). For an LTS $\boldsymbol{L} = \{l_0, l_1, \ldots, l_K\}$, the 2-tuple representing the information equivalent to the result of the symbolic aggregation $\beta \in [0, K]$ is obtained using the mapping:

$$\Delta : [0, K] \rightarrow \boldsymbol{L} \times [-0.5, 0.5)$$

$$\Delta(\beta) = (l_k, \kappa), \text{ with } \begin{cases} l_k, k = round\ (\beta), \\ \kappa = \beta - k, \kappa \in [-0.5, 0.5). \end{cases}$$

Definition 2.5. (Herrera and Martínez, 2000). Consider an LTS $\boldsymbol{L} = \{l_0, l_1, \ldots, l_K\}$ and a 2-tuple (l_k, κ), there exists an inverse function Δ^{-1} that returns the 2-tuple to its actual value $\beta \in [0, K]$:

$$\Delta^{-1} : \boldsymbol{L} \times [-0.5, 0.5) \rightarrow [0, K]$$

$$\Delta^{-1}(l_k, \kappa) = \kappa + k = \beta.$$

Definition 2.6. (Herrera and Martínez, 2000). The following rules are used to compare the 2 TL information $A = (l_{k1}, \kappa_1)$ and $B = (l_{k2}, \kappa_2)$:

- if $k1 < k2$, then $A < B$.
- if $k1 = k2$, then.
  1. i. $A = B$, if $\kappa_1 = \kappa_2$, .
  2. ii. $A < B$, if $\kappa_1 < \kappa_2$, .
  3. iii. $A > B$, if $\kappa_1 > \kappa_2$.

Definition 2.7. (Garg, 2018). A PFS over universal set X is a set of ordered pairs that have the form

$$\widetilde{P} = \{\langle x, (\Theta_{\widetilde{P}}(x), \Phi_{\widetilde{P}}(x))\rangle | x \in X\},$$

where $\Theta_{\widetilde{P}}(x) : X \rightarrow [0, 1]$ and $\Phi_{\widetilde{P}}(x) : X \rightarrow [0, 1]$ define the membership grade and the non-membership grade of an element x in $\widetilde{P}$ respectively, holding the condition

$$0 \le (\Theta_{\widetilde{P}}(x))^2 + (\Phi_{\widetilde{P}}(x))^2 \le 1, \text{for all } x \in X.$$

The degree of hesitation of x to $\widetilde{F}$, denoted as $\pi_{\widetilde{P}}(x)$, is related to these two grades by

$$\pi_{\widetilde{P}}(x) = \sqrt[2]{1 - (\Theta_{\widetilde{F}}(x))^2 - (\Phi_{\widetilde{F}}(x))^2}.$$

Definition 2.8. (Garg, 2018). A 2TLPFS has the form

$$\widetilde{P} = \{\langle x, (l_u(x), \mu(x)), (l_v(x), \upsilon(x))\rangle | x \in X\},$$

where $0 \le \Delta^{-1}(l_u(x), \mu(x)) \le K$, $0 \le \Delta^{-1}(l_v(x), \upsilon(x)) \le K$,

Where the 2-tuple (l_u, μ) stands for the linguistic membership grade, the 2-tuple (l_v, υ) stands for the non-membership grade, and $l_u, l_v \in \boldsymbol{L} = \{l_0, l_1, \ldots, l_K\}$ and $\mu, \upsilon \in [-0.5, 0.5)$. The set satisfies the condition

$$0 \le \left(\Delta^{-1}(l_u(x), \mu(x))\right)^2 + \left(\Delta^{-1}(l_v(x), \upsilon(x))\right)^2 \le K^2.$$

For the 2TLPFSs $\{\widetilde{P}_1, \widetilde{P}_2, \ldots, \widetilde{P}_n\}$, $\widetilde{P}_i = [(l_{u_i}, \mu_i), (l_{v_i}, \upsilon_i)]$, the score function, the multiplication by a scalar, and the aggregation operators that will be used in the implementation of the 2 TLP-FWZIC and 2 TLPF-MABAC is given as follows (Akram et al., 2022):

The score function is computed by Eq. (1)

$$S(\widetilde{P}) = \Delta\left\{K\left(\left(\frac{\Delta^{-1}(l_u, \mu)}{K}\right)^2 - \left(\frac{\Delta^{-1}(l_v, \upsilon)}{K}\right)^2\right)\right\}, \Delta^{-1}(S(\widetilde{P})) \in [0, K]. \quad (1)$$

Multiplication of a 2TLPFS by a constant $\omega > 0$

$$\omega \odot \widetilde{P} = \left\{\Delta\left(K\sqrt[2]{1 - \left(1 - \left(\frac{\Delta^{-1}(l_u, \mu)}{K}\right)^2\right)^{\omega}}\right), \Delta\left(K\left(\frac{\Delta^{-1}(l_v, \upsilon)}{K}\right)^{\omega}\right)\right\}. \quad (2)$$

Given a weighting vector $w = [w_1, w_2, \ldots, w_n]$ whose elements $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$, the aggregation operators are defined as given in Eqs. (3) and (4).

The 2 TLPF weighting averaging operator:

$$2TLPFSWA(\widetilde{P}_1, \widetilde{P}_2, \ldots, \widetilde{P}_n) = \left\{\Delta\left(K\sqrt[2]{1 - \prod_{i=1}^{n}\left(1 - \left(\frac{\Delta^{-1}(l_{u_i}, \mu_i)}{K}\right)^2\right)^{\omega_i}}\right), \Delta\left(K\prod_{i=1}^{n}\left(\frac{\Delta^{-1}(l_{v_i}, \upsilon_i)}{K}\right)^{\omega_i}\right)\right\}. \quad (3)$$

The 2 TLPF weighting geometric operator:

$$2TLPFSWG(\widetilde{P}_1, \widetilde{P}_2, \ldots, \widetilde{P}_n) = \left\{\Delta\left(K\prod_{i=1}^{n}\left(\frac{\Delta^{-1}(l_{u_i}, \mu_i)}{K}\right)^{\omega_i}\right), \Delta\left(K\sqrt[2]{1 - \prod_{i=1}^{n}\left(1 - \left(\frac{\Delta^{-1}(l_{v_i}, \upsilon_i)}{K}\right)^2\right)^{\omega_i}}\right)\right\}. \quad (4)$$

The distance between two 2TLPFSs $\widetilde{P}_1 = [(l_{u_1}, \mu_1), (l_{v_1}, \upsilon_1)]$ and $\widetilde{P}_2 = [(l_{u_2}, \mu_2), (l_{v_2}, \upsilon_2)]$ is measured by the following distance formulas:

The Hamming distance (Deng and Gao, 2019):

$$d_H(\widetilde{P}_1, \widetilde{P}_2) = \left\{\frac{1}{2K}\left(|\Delta^{-1}(l_{u_1}, \mu_1) - \Delta^{-1}(l_{u_2}, \mu_2)| + |\Delta^{-1}(l_{v_1}, \upsilon_1) - \Delta^{-1}(l_{v_2}, \upsilon_2)|\right)\right\}. \quad (5)$$

The Euclidean distance (Akram et al., 2022):

Table 1
Linguistic variables for evaluating the criteria.

Linguistic Variable	Numerical-based Score	2TLPFSs
High Significant (HS)	5	$[(l_5, 0), (l_1, 0)]$
Significant (S)	4	$[(l_4, 0), (l_2, 0)]$
Neutral Significant (NS)	3	$[(l_3, 0), (l_3, 0)]$
Low Significant (LS)	2	$[(l_2, 0), (l_4, 0)]$
Very Low Significant (VLS)	1	$[(l_1, 0), (l_5, 0)]$

$$d_E(\widetilde{P}_1, \widetilde{P}_2) = \left\{ \frac{1}{2K} \left(\left| (\Delta^{-1}(l_{u_1}, \mu_1))^2 - (\Delta^{-1}(l_{u_2}, \mu_2))^2 \right| + \left| (\Delta^{-1}(l_{v_1}, \upsilon_1))^2 - (\Delta^{-1}(l_{v_2}, \upsilon_2))^2 \right| \right) \right\}. \tag{6}$$

The LTS $\boldsymbol{L} = \{l_0, l_1, l_2, l_3, l_4, l_5, l_6\}$, $\mathrm{K} = 6$ will be utilized to denote the linguistic term values with 2TLPFS.

3.2. 2-Tuple linguistic pythagorean fuzzy-weighted zero-inconsistency (2 TLP-FWZIC)

The new version of this powerful method (2 TLP-FWZIC) is developed in the following steps.

Step 1: The initial step involves defining and thoroughly discussing the multi-perspective evaluation criteria for integrated ACs. All acquired criteria, including their respective sub-criteria, are systematically categorized based on the types of behaviour and assessment they demand.

Step 2: To assess and determine the significance of the criteria identified in step 1, specialized panels are selected from relevant subject fields, with a focus on the community of individuals involved in the research of ACs in the HVAC field. To ensure that the structured expert judgment (SEJ) panel is composed of suitable experts, a thorough research process is carried out to identify potential candidates. The list of candidates is then narrowed down through a nomination process, resulting in the selection of final panellists. Once the SEJ panel is formed, an evaluation form is provided to collect their consensus for each criterion. This form is carefully designed to facilitate a structured approach to the assessment process. The responses from the panellists are then collected and converted from a linguistic to a numerical scale, as illustrated in Table 1.

$$\widetilde{w}_j = 2TLPFSWA\left(\frac{\mathrm{IMC}\ (\widetilde{\mathrm{Expert}\ 1/\mathrm{C_j}})}{\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{IMC}\ (\mathrm{Expert}\ 1/\mathrm{C_{1j}})}, \frac{\mathrm{IMC}\ (\widetilde{\mathrm{Expert}\ 2/\mathrm{C_j}})}{\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{IMC}\ (\mathrm{Expert}\ 2/\mathrm{C_{2j}})}, \ldots, \frac{\mathrm{IMC}(\widetilde{\mathrm{Expert\ p}/\mathrm{C_j}})}{\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{IMC}\ (\mathrm{Expert\ p}/C_{nj})} \right), \omega_i = \frac{1}{p}. \tag{8}$$

Overall, the SEJ process is a rigorous and reliable method for evaluating the identified criteria. By ensuring that the panellists are experts in their respective fields, this approach yields valuable insights into the significance of the identified criteria, making it an effective way to evaluate and compare different integrated ACs.

Table 2
Constructing the EDM process.

Expert	C_1	C_2	C_n
Expert_1	Significance of C_1	Significance of C_2	Significance of C_n
Expert_2	Significance of C_1	Significance of C_2	Significance of C_n
Expert_p	Significance of C_1	Significance of C_2	Significance of C_n

Step 3: This step describes the formulation and definition of the process for constructing the expert decision matrix (EDM). Table 2 presents the crucial elements of the EDM, namely the selection criteria and the list of alternatives.

According to Table 2, the decision criterion for selection intersects with the SEJ panel. Each selective expert (*Expert_p*) intersects with every selection criterion (C_n), and a score is assigned to each expert based on the corresponding significance level for each criterion. The EDM forms the basis for the subsequent analytical processes included in the proposed 2 TLP-FWZIC and will be further illustrated in the following steps.

Step 4: This step involves applying a 2TLPFSs-based membership function and associated fuzzification processes to the EDM data. The 2TLPFS is characterized by membership and non-membership grades in the form of 2 TLM as demonstrated in Table 1. These grades satisfy the condition of PFSs where the sum of their squares is bounded by one. Based on Table 1, all linguistic variables and numeric scores must be converted to 2TLPFSs, which serve as the variables for each criterion assessed by each expert. Specifically, the expert evaluating ACs criteria is responsible for determining the priority degree of the assessment criterion within the variables evaluated using 2 TL information.

Step 5: This step is composed of five sub-steps to find the weights of the evaluation criteria.

Step 5.1: The 2 TLPF ratio of data is calculated using Equation (2), as shown in Table 3.

$$\frac{IMC\ (\widetilde{Ep/Cj})}{\sum_{j=1}^{n} IMC\ (Ep/Cpj)} \tag{7}$$

where $IMC(\widetilde{Ep/Cj})$ is the degree of importance given by the p^{th} expert to the j^{th} criterion represented by a 2TLPFS, and $\sum_{j=1}^{n} IMC(Ep/Cpj)$ is the sum of the scores of the 2 TLPF degree of importance, obtained by Eq. (1), of the p^{th} expert for the n criteria. Eq. (7) is executed using Eq. (2).

Step 5.2: The weights of the selection criteria are computed in their 2 TLPF form. Using Equation (3), the evaluations of the experts for the criteria are aggregated to find the weights $(\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n)^T$.

Step 5.3: Using Eq. (1), the scores of the weights $(\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n)^T$, found in the previous sub-step, are computed to get the crisp weights $(\overline{w}_1, \overline{w}_2, \ldots, \overline{w}_n)^T$.

Step 5.4: The crisp weights are modified since the score of 2TLPFSs can attain positive or negative values. If all the scores are positive, jump to the next sub-step. Else, the modified weights are computed by:

$$\overline{w}_j' = \overline{w}_j + \sum_{j=1}^{n} |\overline{w}_j|. \tag{9}$$

Table 3
2 TLPF-based EDM ($\widetilde{EDM}$).

Experts	C_1	C_2	C_n
Expert 1	$\frac{\text{IMC}(\widetilde{\text{Expert }1}/C_1)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }1}/C_{1j})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }1}/C_2)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert\_1}}/C_{1j})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }1}/C_n)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }1}/C_{1j})}$
Expert 2	$\frac{\text{IMC}(\widetilde{\text{Expert }2}/C_1)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }2}/C_{2j})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }2}/C_2)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }2}/C_{2j})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }2}/C_n)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }2}/C_{2j})}$
Expert p	$\frac{\text{IMC}(\widetilde{\text{Expert }p}/C_1)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }p}/C_{pj})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }p}/C_2)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }p}/C_{pj})}$	$\frac{\text{IMC}(\widetilde{\text{Expert }p}/C_n)}{\sum_{j=1}^{n}\text{IMC}(\widetilde{\text{Expert }p}/C_{pj})}$

Step 5.5: The crisp weights or the modified crisp weights $\overline{w}_j'$ are normalized to get the final weights $(w_1, w_2, \ldots, w_n)^T$ that satisfy the condition.

3.3. Modified multi-attributive border approximation area comparison (MABAC)

In this section, a modified 2 TLPF-MABAC is developed to process linguistic assessment information accurately. The MABAC is based on measuring the distance from the BAA, which is simply the difference between the weighted rating of an alternative and the BAA. This distance can be positive, negative, or zero implying that an alternative belongs to the UAA, the LAA, or the BAA respectively. When the MABAC method is implemented using Orthopair fuzzy sets, i.e. sets with two contradicting parameters, calculating the distance from the BAA is a major dilemma. This can be attributed to two main reasons.

Firstly, the distance is always a non-negative value, so the alternatives either belong to the BAA or the UAA. For example, consider an LTS with $K = 8$, suppose it is required to find the distance of the ratings $\widetilde{A}_1 = [(l_6, 0), (l_2, 0)]$ and $\widetilde{A}_2 = [(l_2, 0), (l_6, 0)]$ from the $\widetilde{BAA} = [(l_4, 0), (l_4, 0)]$. When applying formula (5) or (6), the distance is calculated as follows:

$$d_H(\widetilde{A}_1, \widetilde{BAA}) = d_H(\widetilde{A}_2, \widetilde{BAA}) = 0.25, d_E(\widetilde{A}_1, \widetilde{BAA}) = d_E(\widetilde{A}_2, \widetilde{BAA}) = 2.$$

Although it is obvious that $\widetilde{A}_1 > \widetilde{BAA}$, higher MD and lower NMD, which means that $\widetilde{A}_1 \in UAA$, and $\widetilde{A}_2 < \widetilde{BAA}$, lower MD and higher NMD, which means that $\widetilde{A}_2 \in LAA$, the distance measures fail to classify $\widetilde{A}_1$ and $\widetilde{A}_2$ regarding their position in the BAA. For this reason, researchers in the previous work on MABAC using Orthopair, or even Orthotriple, fuzzy sets defuzzify before computing the distance (Rahim et al., 2020; Akram et al., 2023b). Defuzzification using a score function might lead to the loss of information which affects the correctness of the results. Score functions have a limitation; equal scores might be obtained for different fuzzy sets as will be later illustrated in the given example. For this reason, the accuracy function is always employed with the score function in ranking for discrimination. Other researchers (Wang et al., 2020a) employ the score function with distance measures to decide the position of the alternative. If the score of an alternative is higher than the score of the BAA then it belongs to the UAA and the distance is set positive. On the other hand, if the score of an alternative is lower than the score of the BAA then it belongs to the LAA, and the distance is set to negative. In the previous example the score of $S(\widetilde{A}_1) = 0.5 \rightarrow \widetilde{A}_1 \in UAA$ and $S(\widetilde{A}_2) = -0.5 \rightarrow \widetilde{A}_2 \in LAA$. However, employing the score function might fail in some cases. For example, for the ratings $\widetilde{A}_3 = [(l_3, 0), (l_3, 0)]$ and $\widetilde{A}_4 = [(l_5, 0), (l_5, 0)]$ the scores are $S(\widetilde{A}_3) = S(\widetilde{A}_4) = 0$. Hence, it is undecided whether they belong to the UAA or the LAA. Moreover, distance formulas might give different values as follows:

$$d_H(\widetilde{A}_3, \widetilde{BAA}) = d_H(\widetilde{A}_4, \widetilde{BAA}) = 0.125, d_E(\widetilde{A}_3, \widetilde{BAA}) = 0.875, d_E(\widetilde{A}_4, \widetilde{BAA}) = 1.125.$$

Then, the final results will depend upon the distance formula used. This might result in a lack of precision that affects the accuracy of the final results.

Secondly, distance formulas themselves have a drawback. As seen in formulas (5) and (6), the difference in the "support for" represented by the MD and the "support against" represented by the NMD are added together although these differences have different implications. While an increase in the "support for" is an advantage, an increase in the "support against" is a disadvantage. Consequently, the difference in each grade should be handled separately (Sharaf, 2022). From the previous, the difference in each grade will be calculated apart and represented in similar grades. Suppose the rating of an alternative for a criterion is $[(l_u, \mu), (l_\nu, \upsilon)]$ and the BAA is $[(l_{u_B}, \mu_B), (l_{\nu_B}, \upsilon_B)]$. Then, the distance between the membership grade (l_u, μ) of the rating and that of its BAA (l_{u_B}, μ_B) is represented by the 2 tuple as following:

$$(l_{u_d}, \mu_d) = \Delta\left(\left(\left(\Delta^{-1}(l_u, \mu) - \Delta^{-1}(l_{u_B}, \mu_B)\right) / K\right) + 1\right). \tag{10}$$

Here, the difference is kept with its sign to denote an increase or a decrease in the grade than its peer in the BAA. If the difference is positive, the value $\{((\Delta^{-1}(l_u, \mu) - \Delta^{-1}(l_{u_B}, \mu_B)) / K) + 1\}$ will be more than one, indicating a higher "support for" which is a merit for an alternative. Otherwise, if the difference is negative, this value will be less than one, indicating a lower "support for" which is a demerit for an alternative. In both cases, the maximum difference $|\Delta^{-1}(l_u, \mu) - \Delta^{-1}(l_{u_B}, \mu_B)|$ is bounded by K. Concurrently, the distance between the non-membership grade (l_ν, υ) of the rating of an alternative and that of the BAA (l_{ν_B}, υ_B) is given by the 2 tuple as following:

$$(l_{\nu_d}, \upsilon_d) = \Delta\left(\left(\left(\Delta^{-1}(l_\nu, \upsilon) - \Delta^{-1}(l_{\nu_B}, \upsilon_B)\right) / K\right) + 1\right). \tag{11}$$

Unlike membership grade, if the difference is positive, the value $\{\Delta^{-1}(l_\nu, \upsilon) - \Delta^{-1}(l_{\nu_B}, \upsilon_B)\}$ will be more than one, indicating an increase in the "support against" which is a demerit for an alternative. Else if the difference is negative, this value will be less than one, indicating a decrease in the "support against" which is a merit for an alternative. Similar to (10), the maximum difference $|\Delta^{-1}(l_\nu, \upsilon) - \Delta^{-1}(l_{\nu_B}, \upsilon_B)|$ is bounded by K. On this account, the distance between two 2TLPFSs $\widetilde{P}_1 = [(l_{u_1}, \mu_1), (l_{\nu_1}, \upsilon_1)]$ and $\widetilde{P}_2 = [(l_{u_2}, \mu_2), (l_{\nu_2}, \upsilon_2)]$ will be represented by $d(\widetilde{P}_1, \widetilde{P}_2) = [(l_{u_d}, \mu_d), (l_{\nu_d}, \upsilon_d)]$.

Proposition 1. *The distance between 2TLPFSs denoted by*

$$d(\widetilde{P}_1, \widetilde{P}_2) = [(l_{u_d}, \mu_d), (l_{\nu_d}, \upsilon_d)]$$

$$= \left[\Delta\left(\frac{(\Delta^{-1}(l_{u_1}, \mu_1) - \Delta^{-1}(l_{u_2}, \mu_2))}{K} + 1\right), \Delta\left(\frac{(\Delta^{-1}(l_{\nu_1}, \upsilon_1) - \Delta^{-1}(l_{\nu_2}, \upsilon_2))}{K} + 1\right)\right]. \tag{12}$$

is a 2TLPFS.

Proof: *For an LTS* $\boldsymbol{L} = \{l_0, l_1, \ldots, l_K\}$ *with* $K > 2$.
Since $-K \leq (\Delta^{-1}(l_{u_1}, \mu_1) - \Delta^{-1}(l_{u_2}, \mu_2)) \leq K$,
Then, $0 \leq \frac{(\Delta^{-1}(l_{u_1}, \mu_1) - \Delta^{-1}(l_{u_2}, \mu_2))}{K} + 1 \leq 2$.
Similarly, $-K \leq (\Delta^{-1}(l_{\nu_1}, \upsilon_1) - \Delta^{-1}(l_{\nu_2}, \upsilon_2)) \leq K$.
And $0 \leq \frac{(\Delta^{-1}(l_{\nu_1}, \upsilon_1) - \Delta^{-1}(l_{\nu_2}, \upsilon_2))}{K} + 1 \leq 2$.

Then, (l_{u_d}, μ_d) *and* (l_{v_d}, υ_d) *satisfy the condition*

$$0 \le \Delta^{-1}\left(l_{u_d}, \mu_d\right), \Delta^{-1}\left(l_{v_d}, \upsilon_d\right) \le \mathrm{K}.$$

We also have

$$0 \le \left(\Delta^{-1}\left(l_{u_d}, \mu_d\right)\right)^2 + \left(\Delta^{-1}\left(l_{v_d}, \upsilon_d\right)\right)^2 \le 8,$$

and (l_{u_d}, μ_d) *and* (l_{v_d}, υ_d) *also, satisfy the condition*

$$0 \le \left(\Delta^{-1}\left(l_{u_d}, \mu_d\right)\right)^2 + \left(\Delta^{-1}\left(l_{v_d}, \upsilon_d\right)\right)^2 \le \mathrm{K}^2.$$

The distance $d(\widetilde{P}_1, \widetilde{P}_2)$ satisfies the conditions of a 2TLPFS for $\mathrm{K} > 2$.

In the conventional MABAC, the weights of the criteria are applied to the decision matrix to get the weighted decision matrix. After that, the distance is measured between the weighted ratings of an alternative and the BAA for each criterion. So the impact of the weight is not reflected in the distance since it is measured within the same criterion. To make the weighting process more discriminating, instead of applying the weights of the criteria to the decision matrix, the weights will be applied when aggregating the distances of the ratings of the alternatives from the BAA of the assessment criteria. In this way, each distance is multiplied by the weight of the corresponding criterion when summing the elements of the distance matrix. For an MCDM problem with n alternatives $\{A_1, A_2, \ldots, A_n\}$, m criteria $\{C_1, C_2, \ldots, C_m\}$ with weights $\{w_1, w_2, \ldots, w_m\}$ that satisfy $w_j \in [0,1]$ and $\sum_{j=1}^{m} w_j = 1$, the modified MABAC method is demonstrated through the following steps.

Step 1: Form the evaluation matrix $\widetilde{\mathbf{R}} = [\widetilde{r}_{ij}]$, whose elements are the ratings of the alternatives according to their performance for the assessment criteria using the linguistic variables given in Table 1.

$\widetilde{\mathbf{R}}$	C_1	C_2	…	C_m
A_1	$\widetilde{r}_{11}$	$\widetilde{r}_{12}$	…	$\widetilde{r}_{1m}$
A_2	$\widetilde{r}_{21}$	$\widetilde{r}_{22}$	…	$\widetilde{r}_{2m}$
⋮	…	…	…	…
A_n	$\widetilde{r}_{n1}$	$\widetilde{r}_{n2}$	…	$\widetilde{r}_{nm}$

Step 2: This step depends on how linguistic information describes a criterion since the criteria in most cases are classified to benefit and cost criteria. If the cost criteria are positively evaluated, for example, the price is rated as "good", normalization is not needed. On the contrary, if the cost criteria are negatively evaluated, for example, the price is rated as "bad" or "high", normalization is a must and it is conducted by using the complement of the linguistic term. The complement of a 2TLPFS $\widetilde{P} = [(l_u, \mu), (l_v, \upsilon)]$ is defined as $\widetilde{P}^c = [(l_v, \upsilon), (l_u, \mu)]$.

Step 3: Compute the border approximation area for each criterion using Eq. (4), hence the border approximation area matrix $\widetilde{\mathbf{B}}$.

$\widetilde{\mathbf{B}}$	C_1	C_2	…	C_m
	$\widetilde{b}_1$	$\widetilde{b}_2$	…	$\widetilde{b}_m$

Where $\widetilde{b}_j = (\prod_{i=1}^{n} \widetilde{r}_{ij})^{1/n} = 2TLPFSWG(\widetilde{r}_{1j}, \widetilde{r}_{2j}, \ldots, \widetilde{r}_{nj}), w_i = 1/n.$

Step 4. Compute the 2 TLPF distance matrix $\widetilde{\mathbf{D}}$.

$\widetilde{\mathbf{D}}$	C_1	C_2	…	C_m
A_1	$\widetilde{d}(\widetilde{r}_{11}, \widetilde{b}_1)$	$\widetilde{d}(\widetilde{r}_{12}, \widetilde{b}_2)$	…	$\widetilde{d}(\widetilde{r}_{1m}, \widetilde{b}_m)$
A_2	$\widetilde{d}(\widetilde{r}_{21}, \widetilde{b}_1)$	$\widetilde{d}(\widetilde{r}_{22}, \widetilde{b}_2)$	…	$\widetilde{d}(\widetilde{r}_{2m}, \widetilde{b}_m)$
⋮	…	…	…	…
A_n	$\widetilde{d}(\widetilde{r}_{n1}, \widetilde{b}_1)$	$\widetilde{d}(\widetilde{r}_{n2}, \widetilde{b}_2)$	…	$\widetilde{d}(\widetilde{r}_{nm}, \widetilde{b}_m)$

Where $\widetilde{d}(\widetilde{r}_{ij}, \widetilde{b}_j)$ is the 2 TLPF- the distance between the rating of an alternative and the BAA of the j^{th} criterion.

Step 5: Compute the total distance for each alternative using Eq. (3).

$$\widetilde{T}(A_i) = \left(\sum_{j=1}^{m} \widetilde{d}(\widetilde{r}_{ij}, \widetilde{b}_j)\right)^{w_j} = 2TLPFSWA(\widetilde{d}(\widetilde{r}_{i1}, \widetilde{b}_1), \widetilde{d}(\widetilde{r}_{i2}, \widetilde{b}_2), \ldots, \widetilde{d}(\widetilde{r}_{im}, \widetilde{b}_m)),$$

where w_j is the weight of the j^{th} *the* criterion in the weighting vector $\mathrm{w} = [w_1, w_2, \ldots, w_m]$ that satisfies $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$.

Step 6: Find the score of the total distance for the alternatives and rank them. Using Eq. (1), the scores of the alternatives $S(\widetilde{T}(A_i))$ are calculated, and then the alternatives are ranked in descending order. The best alternative is the one with the highest score.

4. Integrated active cooling systems (ACs)

In this section, we will delve into the formulation and discussion of a multi-perspective decision matrix for integrated ACs. This matrix is based on two key elements: the list of alternatives for ACs and the criteria used to evaluate them.

4.1. ACs alternatives

The first element of AC integration refers to the list of options being considered, which includes different brands, models, or configurations of AC systems. Decision-makers consider multiple alternatives to compare and contrast the benefits and drawbacks of each option. There are two main types of ACs based on their energy source: electric-powered ACs and thermal-powered ACs (which use heat or gas).

4.1.1. Electricity-based ACs

The most popular AC system used in homes today is the electricity-based VC system, which can be found in different forms such as split, packaged, ducted, ductless, stationary, and portable (Pezzutto et al., 2022b). This ACs category has different configurations as follows.

4.1.1.1. Producing cold air. The classifications for systems that generate cold air are divided into two primary groups. These include split systems and packaged systems.

Split systems: Three types of split systems are classified including mono-split systems, multi-split systems, and variable refrigerant flow (VRF) systems. Firstly, the mono-split system is a basic air conditioning unit that is suitable for small areas or single rooms. It consists of one indoor unit (with an evaporator) and one outdoor unit (with a condenser, compressor, and fan) (Moura et al., 2020). Secondly, an air conditioner that comprises one or more indoor units and an outdoor unit is referred to as a multi-split air conditioner (Zhou et al., 2023). The mono and multi-split systems can be categorized into ducted and ductless types (Bhandari and Fumo, 2022). Thirdly, VRF systems use one outdoor unit and multiple indoor units to provide both cooling and heating. The electronic expansion valve (EEV) controls the mass flow rate and can be adjusted based on thermal measurements. These systems can also function as reversible heat pumps. Two types of VRF systems are the 2-pipe system and the 3-pipe system (Hernandez and Fumo, 2020). The 2-pipe system operates in either cooling or heating mode for the entire system, while the 3-pipe system can provide heating and cooling in different zones, making it more popular due to greater control.

Packaged units: Packaged air conditioners, also known as unitary systems, are pre-assembled at the factory site and contain the evaporator, condenser, and compressor in a single box. They can also be integrated with thermal energy storage (*TES*) systems, providing energy savings and improving the integration of renewable energy systems. Packaged ACs can be classified into four main types (Parkinson et al., 2021). Firstly, window units are compact and can be installed in standard window frames for small cooling capacities. Secondly, terminal units are installed under a window and connect the condenser and evaporator through a grilled opening in the wall. Thirdly, portable units are easily carried inside a building with a tube to remove heated air outside. Lastly, rooftop units are larger systems that use ducts to deliver cold air into the building and are commonly used in restaurants, homes, and small halls.

4.1.1.2. Producing cold water. Chillers are large air conditioning units that cool indoor air by circulating chilled water through a network of pipes and heat exchangers. Chillers are typically powered by electricity, but can also use renewable energy sources. They come in a variety of sizes and systems to cool all types of buildings, and the heat is removed through the condenser, which can be air-cooled, water-cooled, or evaporative-cooled (Elnagar et al., 2023). First, air-cooled chillers use one or more fans to cool the condenser coils and reject heat generated by the refrigerant directly to the outside air. Second, water-cooled chillers reject heat to water, which is then circulated to a dry-cooler or wet-cooling tower. Water-cooled chillers include several types, such as dry coolers, wet cooling towers, geothermal boreholes, and aquifer thermal energy storage (*ATES*). Third, hybrid evaporative air-cooled condensers combine a cooling tower and an air-cooled refrigerant condenser. They use adiabatic cooling where water cascades over the evaporative condenser's surface and the air is drawn through it. They are similar to swamp coolers but include an additional cooling component (Hajidavalloo and Eghtedari, 2010).

4.1.2. Thermal energy-based ACs

The amount of electrical energy required for thermal energy-driven cooling systems is typically insignificant. Within this category of air conditioners, there are various types available, such as sorption chillers, ejectors, and desiccant systems. Firstly, there are two types of sorption cooling systems (Kuczyńska and Szaflik, 2010): absorption chillers use lithium Bromide (LiBr) or water as the absorbent fluid and water or ammonia (NH3) as the refrigerant, while adsorption chillers use silica gel, activated carbon, or zeolites as the adsorbents and water as the refrigerant. Secondly, ejector-type sorption cooling systems use a cycle of components including an evaporator, generator, ejector, condenser, expansion valve, and circulation pump (Chen et al., 2013). Desiccant cooling systems are heat-driven and can handle sensible and latent heat loads independently. They use either solid or liquid desiccant materials to remove moisture from warm, humid air and can be stored when a heat source is not available for regeneration (Maurya et al., 2014; Sarbu and Sebarchievici, 2016).

4.2. ACs evaluation criteria

The second element, AC's evaluation criteria, outlines the factors that will be used to assess the performance of each alternative. These criteria include performance and technical perspectives.

4.2.1. Performance criteria (C1)

Energy performance (system efficiency) ($C_{1.1}$)*:* The energy performance of air conditioners is measured by standards such as energy efficiency ratio (EER). Seasonal EER (SEER) is an average efficiency value calculated from EER measurements at different outdoor temperatures. A higher EER or coefficient of performance (*COP*) indicates a more efficient unit (Wang et al., 2020b).

The flexibility of the system ($C_{1.2}$)*:* The flexibility criterion is used to measure the performance of air conditioners and consists of two sub-criteria. The first sub-criterion ($C_{1.2.1}$) is energy source flexibility, which involves integrating multi-energy systems with different sources, including renewable energy. The second sub-criterion ($C_{1.2.2}$) is integration with secondary systems such as fan coil units and radiant floor systems (Elnagar et al., 2023).

Climate resilience ($C_{1.3}$)*:* In this performance criterion, the first sub-criterion ($C_{1.3.1}$) is focused on the effect of extreme events, such as heatwaves, on cooling systems and their ability to maintain indoor thermal comfort. The second sub-criterion ($C_{1.3.2}$) examines the resilience of cooling systems to power outages and their ability to recover from such failures (Attia, 2023).

Building type ($C_{1.4}$)*:* Various types of AC systems are installed in different types of buildings, including industrial, commercial, residential, and institutional buildings (Elnagar et al., 2023).

TRL ($C_{1.5}$)*:* The final performance criterion is utilized to evaluate the maturity of a technology. The TRL system ranges from 1 to 9, with 9 representing the most advanced technology (Elnagar et al., 2023).

4.2.2. Technical criteria (C2)

Reversibility (REV) ($C_{2.1}$)*:* The REV criterion is concerned with the ability of an air conditioning system to function as a heat pump. This refers to the system's capability to reverse the direction of its refrigeration cycle, allowing it to transfer heat from the outdoor environment to the indoor space, rather than removing heat from the indoor space and releasing it outside (Prasad et al., 2019).

Recovery (REC) ($C_{2.2}$)*:* The REC technical criterion pertains to the system's ability to recover heat at the condenser. This involves the simultaneous process of heating and cooling, where the recovered heat from the cooling process is redirected and utilized for heating purposes (Nguyen and Shabani, 2020).

Passivity (PAS) ($C_{2.3}$)*:* The criterion refers to the system's potential to achieve passive cooling. Passive cooling utilizes natural and passive methods, such as ventilation and shading, to maintain comfortable indoor temperatures (Nasef et al., 2019).

System capacity range ($C_{2.4}$)*:* The criterion refers to the range of cooling capacity that an air conditioning system can provide. It is a technical specification that determines the maximum and minimum cooling output of the system (Elnagar et al., 2023).

4.3. Multi-perspective decision matrix

The multi-perspective decision matrix brings the two predefined elements (ACs alternatives and criteria) together comprehensively and systematically. It enables decision-makers to evaluate each alternative against the established criteria, considering multiple perspectives and identifying a conflict between different factors. Table 4 presents the formulation of the multi-perspective decision matrix for ACs by taking into account the intersection of alternative ACs and corresponding performance and technical criteria.

As seen from Tables 4 and it should be considered that alternative selection differs based on the criteria considered. In the context of this research, criteria ($C_{1.1}$, $C_{1.2.1}$, $C_{1.2.2}$, $C_{1.3.1}$, $C_{1.3.2}$, $C_{1.4}$, and $C_{1.5}$) were based on the performance of the ACs, while criteria $C_{2.1}$, $C_{2.2}$, $C_{2.3}$, and $C_{2.4}$) were based on technical characteristics of the ACs manufacturing, the table also shows the characteristics of the alternatives (ACs). Evaluation of the alternatives for criteria $C_{2.1}$,$C_{2.2}$, $C_{2.3}$,$C_{2.4}$ was carried out based on the technical characteristics as stated by the manufacturer of the ACs, while the evaluation of the alternatives according to criteria $C_{1.1}$, $C_{1.2.1}$, $C_{1.2.2}$, $C_{1.3.1}$, $C_{1.3.2}$, $C_{1.4}$, and $C_{1.5}$ was based on the experiential knowledge of the decision maker in the position of ACs.

Table 4
ACs multi-perspective decision matrix.

ACs					C_1							C_2			
					$C_{1.1}$	$C_{1.2}$		$C_{1.3}$		$C_{1.4}$	$C_{1.5}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{2.4}$
						$C_{1.2.1}$	$C_{1.2.2}$	$C_{1.3.1}$	$C_{1.3.2}$						
Electricity-based ACs	Producing cold air	Split systems	Mono split systems	A1: Ducted	H	M	M	H	L	AT	9	Y	N	N	LA
				A2: Ductless	H	M	M	H	L	AT	9	Y	N	N	LA
			Multi-split systems	A3: Ducted	H	M	M	H	L	AT	9	Y	N	N	LA
				A4: Ductless	H	M	M	H	L	AT	9	Y	N	N	LA
			VRF	A5: 2-Pipe	H	L	M	M	L	LB	9	Y	N	N	LA
				A6: 3-Pipe	H	L	M	M	L	LB	9	Y	Y	N	LA
		Packaged units	A7: Window		H	L	L	L	L	R	9	Y	N	N	L
			A8: Portable		H	L	L	L	L	AT	9	Y	N	N	M
			A9: Rooftop		H	L	M	H	L	LB	9	Y	N	N	LA
	Producing chilled water		A10: Air-cooled		H	M	H	M	L	AT	9	Y	N	Y	LA
			Water-cooled	A11: Dry cooler	H	M	H	M	M	AT	9	N	Y	Y	LA
				A12: Wet cooling tower	H	M	H	H	M	LOB	9	N	Y	Y	LA
				A13: Geothermal borehole	H	M	H	H	M	AT	9	Y	Y	Y	LA
				A14: ATES	H	M	H	H	M	LOB	9	Y	Y	Y	LA
			A15: Evaporative-cooled		H	M	H	H	L	AT	9	N	N	N	LA
Thermal energy-based ACs	Sorption chiller	A16: Adsorption			L	H	L	M	M	AT	3–9	Y	Y	N	LA
		A17: Absorption			L	H	L	M	M	AT	3–9	Y	Y	N	LA
	A18: Ejector				L	H	H	M	H	AT	3	N	Y	N	L
	Desiccant systems	A19: Liquid			H	H	H	L	M	AT	3–4	N	N	N	LA
		A20: Solid			H	H	H	L	M	AT	3–4	N	N	N	LA

ACs = active cooling systems, L = low, M = medium, H = high, LA = large, AT = all types, LB = large buildings, R = residential, LOB = large office buildings, Y = yes, and N = no.

Table 5
Criteria weighting (level 1).

Criteria	Performance Criteria	Technical Details
Expert 1	70%	30%
Expert 2	45%	55%
Expert 3	63%	37%

Table 6
Performance criteria importance determination by experts.

Criteria	Energy Performance		The flexibility of the System		Climate Resilience		Building Type		Technology Readiness Level	
(E1)	5	VH	5	VH	3	M	2	ML	3	M
(E2)	4	H	3	M	4	H	1	L	4	H
(E3)	5	VH	4	H	2	ML	2	ML	3	M

5. Experimental results

This section presents the research results for criteria weighing using 2 TLP-FWZIC, followed by selecting the most suitable ACs using 2 TLPF-MABAC.

5.1. Weighting determination

This section presents the weighting results obtained from the application of 2 TLP-FWZIC to the technical and performance criteria utilized in the selection of suitable ACs. The generation of these results involved several steps, as discussed in Section 3. These steps commenced with the inclusion of the evaluation criteria outlined in Section 4. Subsequently, the criteria were assessed for their importance on two separate levels. The first level involved the use of a ratio basis, as the criteria were represented by two distinct aspects: performance and technical, as shown in Table 5.

As shown in Table 5, two distinct aspects of criteria are presented: the first aspect pertains to performance criteria, which were assessed by the same experts as the other aspect. It is evident that out of the three experts (expert 1 and 3), ($n = 2/3$) preferred performance criteria over the technical ones, with ratios of *70%* and *63%* respectively. However, expert 2 had a lower preference for performance criteria, with a ratio of

Table 7
Final Weight for Perf ormance Criteria.

Criteria	Identifier	Fuzzy weight	Score	Modified Score	Weight
Energy performance	$C_{1.1}$	$[(l_3, 0.3045), (l_4, 0.3551)]$	−0.0562	10.8685	0.2487
The flexibility of the system	$C_{1.2}$	$[(l_3, -0.3788), (l_4, 0.0293)]$	−1.5607	9.3639	0.2143
Climate Resilience	$C_{1.3}$	$[(l_2, 0.1217), (l_4, 0.4932)]$	−2.6146	8.3100	0.1902
Building Type	$C_{1.4}$	$[(l_1, 0.0461), (l_5, 0.3189)]$	−4.5328	6.3919	0.1463
Technology Readiness level	$C_{1.5}$	$[(l_2, 0.3197), (l_4, 0.2829)]$	−2.1604	8.7643	0.2006

Table 8
All Crite ria Final Weights (All Levels).

Criteria (level 1)		Criteria (Level 2)	Criteria (Level 3)	Weight
Performance (C_1)	0.59	Energy performance ($C_{1.1}$)		0.1467
		The flexibility of the system (**$C_{1.2}$**)	Energy source flexibility (**$C_{1.2.1}$**)	0.0632
			Integration with secondary systems (**$C_{1.2.2}$**)	0.0632
		Climate Resilience (**$C_{1.3}$**)	Heat waves (**$C_{1.3.1}$**)	0.0561
			Power outages (**$C_{1.3.2}$**)	0.0561
		Building Type (**$C_{1.4}$**)		0.0863
		Technology Readiness level (**$C_{1.5}$**)		0.1184
Technical (**C_2**)	0.41	Possibility to reverse the machine. (**$C_{2.1}$**)		0.1025
		Possibility to recover heat at the condenser. (**$C_{2.2}$**)		0.1025
		Possibility to make passive cooling. (**$C_{2.3}$**)		0.1025
		System Capacity Range (**$C_{2.4}$**)		0.1025

45%. Conversely, expert 2 expressed a higher preference for technical details, with a ratio of *55%*, while expert 1 and 3 showed a lesser preference for these criteria compared to performance, with ratios of *30%* and *37%* respectively. It is important to note that the importance of these criteria was reevaluated for the sub-criteria (associated with performance criteria) based on the opinions of the same three technology experts used previously for the assessment of main criteria. According to the experts' responses, the linguistic terms were transformed into numerical scales using Table 1. These processes were then followed by EDM, as presented in Table 6.

As seen from Table 6, the preferences of the previous three experts were obtained for the (performance) sub-criteria using linguistic variables and numerical scale for each criterion. The evaluation carried out here was applied using a hybrid approach that combined fuzzy weights with 2TLPFSs to address uncertainties and inconsistencies in evaluations of the DMs. Each DM provided its evaluation for each criterion, resulting in a matrix of 5 criteria by three DMs. It can be seen that evaluation scores showed varying degrees of agreement among the DMs for the different criteria. For example, the first criterion $C_{1.1}$_energy performance received a (high significance) evaluation score from (experts 1 and 3) while (expert 2) gave (significance) score, indicating a generally high level of agreement among DMs. However, criterion $C_{1.4}$_building type received mixed evaluation scores from the DMs based on its technical characteristic, indicating a lower level of agreement. Overall, the table provides a useful summary of performance) sub-criteria by multiple decision-makers using a hybrid fuzzy approach. This highlights the importance of considering uncertainties and inconsistencies in DMs' evaluations of DMs when making complex decisions, such as when selecting the most optimal ACs. After constructing the EDM represented in Table 6, the following step includes using 2TLPFSs, whereby the crisp values are transformed into their fuzzy numbers represented in Table 1. The EDM fuzzification process was completed upon completion of the previous process. The following step includes each expert's mean preference computed using Eq. (7) and Eq. (8) to generate a fuzzy weight. Subsequently, the defuzzification process was established, resulting in crisp weights which are then modified and normalized to the final weight, as presented in Table 7.

As presented in Table 7, all sub-evaluation criteria related to performance used in the selection of the ACs were weighted using 2 TLP-FWZIC. Several observations can be made, including the determination of each criterion's importance. For instance, $C_{1.1}$_energy performance was identified as the most significant criterion with a weighting value of *0.2487*, followed by $C_{1.2}$_flexibility of the system with a weighting value of *0.2143*, and $C_{1.3}$_climate resilience with a weighting value of *0.2006*. The two sub-criteria with the lowest weights were $C_{1.3}$_climate resilience at *0.1902* and $C_{1.4}$_building type with the lowest value of *0.1463*. These weighting results underwent an additional process where their values were scaled to align with the main criteria. Furthermore, during the analysis and weighting stage, multiple levels of criteria were observed, and the final weighting results for all criteria across these levels, to be used in the final selection, are presented in Table 8.

As seen from Table 8, three levels of criteria weighting were presented. The first level pertained to the main criteria (C_1_performance and C_2_technical), followed by second-level criteria, including $C_{1.1}$_energy performance, $C_{1.2}$_flexibility of the system, $C_{1.3}$_climate resilience, $C_{1.4}$_building type, and $C_{1.5}$_technology readiness level, for C_1. The technical sub-criteria (C_2) comprised $C_{2.1}$_possibility to reverse the machine, $C_{2.2}$_possibility to recover heat at the condenser, $C_{2.3}$_possibility to make passive cooling, and $C_{2.4}$_system capacity range. Only C_1 had a third level of criteria, which encompassed energy source flexibility and integration with secondary systems falling under the $C_{1.2}$ sub-criteria, as well as heat waves and power outages belonging to the $C_{1.3}$ sub-criteria. Measures were undertaken for these criteria across the levels. Firstly, the main level criteria (C_1 and C_2) were weighted based on expert references, resulting in the former being assigned a weight of *0.59* and the latter being assigned a weight of *0.41*. For the C_2 criteria ($C_{2.1}$ – $C_{2.4}$), their weighting results were obtained by equally distributing the main criteria (C_2) weight into four new scaled weights of *0.1025* for each C_2 sub-criterion. This approach was chosen based on discussions with experts, who emphasized that these technical criteria are equally important and should not be favored against each other. Therefore, the decision was made to distribute the main criteria weight equally among them. For the C_1 criteria, a combination of processes was

Table 10
2TLPFSs transformation numbers.

Likert Scale	2TLPFSs
5	$[(l_5, 0), (l_1, 0)]$
4	$[(l_4, 0), (l_2, 0)]$
3	$[(l_3, 0), (l_3, 0)]$
2	$[(l_2, 0), (l_4, 0)]$
1	$[(l_1, 0), (l_5, 0)]$

Table 9
Decision matrix for ACs selection.

Alternative	Criteria										
	Performance Criteria							Technical Criteria			
	$C_{1.1}$	$C_{1.2.1}$	$C_{1.2.2}$	$C_{1.3.1}$	$C_{1.3.2}$	$C_{1.4}$	$C_{1.5}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{2.4}$
A1	5	3	3	5	1	5	4	3	1	1	5
A2	5	3	3	5	1	5	4	3	1	1	5
A3	5	3	3	5	1	5	4	3	1	1	5
A4	5	3	3	5	1	5	4	3	1	1	5
A5	5	1	3	3	1	4	4	3	1	1	5
A6	5	1	3	3	1	4	4	3	3	1	5
A7	5	1	1	1	1	2	4	3	1	1	1
A8	5	1	1	1	1	5	4	3	1	1	3
A9	5	1	3	5	1	4	4	3	1	1	5
A10	5	3	5	3	1	5	4	3	1	3	5
A11	5	3	5	3	3	5	4	1	3	3	5
A12	5	3	5	5	3	3	4	1	3	3	5
A13	5	3	5	5	3	5	4	3	3	3	5
A14	5	3	5	5	3	3	4	3	3	3	5
A15	5	3	5	5	1	5	4	1	1	1	5
A16	1	5	1	3	3	5	5	3	3	1	5
A17	1	5	1	3	3	5	5	3	3	1	5
A18	1	5	5	3	5	5	2	1	3	1	1
A19	5	5	5	1	3	5	3	1	1	1	5
A20	5	5	5	1	3	5	4	1	1	1	5

Table 11
2 TLPF decision matrix.

A	C_1	C_2	C_3	C_4	C_5	C_6
A_1	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_2	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_3	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_4	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_5	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_4,0),(l_2,0)]$
A_6	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_4,0),(l_2,0)]$
A_7	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_2,0),(l_4,0)]$
A_8	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_9	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_4,0),(l_2,0)]$
A_{10}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{11}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{12}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$
A_{13}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{14}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$
A_{15}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{16}	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{17}	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{18}	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{19}	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{20}	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_5,0),(l_1,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$

A	C_7	C_8	C_9	C_{10}	C_{11}
A_1	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_2	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_3	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_4	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_5	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_6	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_7	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$
A_8	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$
A_9	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{10}	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{11}	$[(l_4,0),(l_2,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{12}	$[(l_4,0),(l_2,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{13}	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{14}	$[(l_4,0),(l_2,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_5,0),(l_1,0)]$
A_{15}	$[(l_4,0),(l_2,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{16}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{17}	$[(l_5,0),(l_1,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{18}	$[(l_2,0),(l_4,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$
A_{19}	$[(l_3,0),(l_3,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$
A_{20}	$[(l_4,0),(l_2,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_1,0),(l_5,0)]$	$[(l_5,0),(l_1,0)]$

Table 12
BAA matrix.

Criteria	BAA
C_1	$[(l_4, -0.0724),(l_3, -0.4352)]$
C_2	$[(l_3, -0.4100),(l_4, -0.3968)]$
C_3	$[(l_3, 0.0306),(l_3, 0.2625)]$
C_4	$[(l_3, 0.0306),(l_3, 0.2625)]$
C_5	$[(l_2, -0.3181),(l_4, 0.3941)]$
C_6	$[(l_4, 0.3889),(l_2, -0.1888)]$
C_7	$[(l_4, -0.1055),(l_2, 0.1745)]$
C_8	$[(l_2, 0.1577),(l_4, -0.0788)]$
C_9	$[(l_2, -0.4482),(l_4, 0.4996)]$
C_{10}	$[(l_1, 0.3161),(l_5, -0.2850)]$
C_{11}	$[(l_4, 0.1494),(l_2, 0.2863)]$

applied. Firstly, the group consisting of $C_{1.1}$_energy performance, $C_{1.4}$_building type, and $C_{1.5}$_technology readiness level was weighted by scaling their generated 2 TLP-FWZIC weight with their main criteria (C_1) to obtain their final scaled weight. The same multiplication and scaling process was followed for $C_{1.2}$_flexibility of the system and $C_{1.3}$_climate resilience, but their final weight was equally distributed among their third-level criteria. This resulted in the $C_{1.2}$ wt being equally distributed for $C_{1.2.1}$_energy source flexibility and $C_{1.2.2}$_integration with secondary systems, each with a weight of *0.0632*, and the $C_{1.3}$ wt being equally distributed for $C_{1.3.1}$_heat waves and $C_{1.3.2}$_power outages, each with a weight of *0.0561*. All these weights for the criteria are utilized alongside modified MABAC in the subsequent section.

5.2. ACs selection

After completing the weighting stage using 2 TLP-FWZIC, all the necessary conditions and parameters were established to initiate the evaluation and selection process of ACs using the modified version of the 2 TLPF-MABAC method. This selection process considers all three levels of evaluation criteria and their intersection with the alternatives (ACs) employed in this study, as shown in Table 9.

As shown in Tables 9 and it is important to note that alternative selection varies based on the considered criteria. In the context of this research, criteria ($C_{1.1}$, $C_{1.2.1}$, $C_{1.2.2}$, $C_{1.3.1}$, $C_{1.3.2}$, $C_{1.4}$, and $C_{1.5}$) were based on the performance of the ACs, while criteria ($C_{2.1}$, $C_{2.2}$, $C_{2.3}$, and $C_{2.4}$) were based on the technical characteristics of the ACs' manufacturing. The table also presents the characteristics of the alternatives (ACs). The evaluation of the alternatives for criteria $C_{2.1}$, $C_{2.2}$, $C_{2.3}$, and $C_{2.4}$ was conducted based on the technical characteristics provided by the manufacturer of the ACs. On the other hand, the evaluation of the alternatives for criteria $C_{1.1}$, $C_{1.2.1}$, $C_{1.2.2}$, $C_{1.3.1}$, $C_{1.3.2}$, $C_{1.4}$, and $C_{1.5}$ was based on the experiential knowledge of the decision maker responsible for selecting the ACs. The evaluation of alternatives based on criteria C_2 and C_3 utilized the fuzzified Likert scale, which is presented in Table 6. The 2 TLPF-MABAC method is then employed to select the most optimal ACs. According to 2 TLPF-MABAC, a total of 20 ACs are evaluated for selection across 11 criteria. The process starts with

Table 13
Distance of each alternative from the BAA matrix in 2 TLPF

A	C_1	C_2	C_3	C_4
A_1	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_2	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_3	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_4	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_5	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,-0.2650)(l_1,0.2328)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_6	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,-0.2650)(l_1,0.2328)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_7	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,-0.2650)(l_1,0.2328)]$	$[(l_1,-0.3384)(l_1,0.2896)]$	$[(l_1,-0.3384)(l_1,0.2896)]$
A_8	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,-0.2650)(l_1,0.2328)]$	$[(l_1,-0.3384)(l_1,0.2896)]$	$[(l_1,-0.3384)(l_1,0.2896)]$
A_9	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,-0.2650)(l_1,0.2328)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_{10}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_{11}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_{12}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_{13}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_{14}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_{15}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.0683)(l_1,-0.1005)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,0.3282)(l_1,-0.3711)]$
A_{16}	$[(l_1,-0.4879),(l_1,0.4059)]$	$[(l_1,0.4017)(l_1,-0.4339)]$	$[(l_1,-0.3384)(l_1,0.2896)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_{17}	$[(l_1,-0.4879),(l_1,0.4059)]$	$[(l_1,0.4017)(l_1,-0.4339)]$	$[(l_1,-0.3384)(l_1,0.2896)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_{18}	$[(l_1,-0.4879),(l_1,0.4059)]$	$[(l_1,0.4017)(l_1,-0.4339)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,-0.0051)(l_1,-0.0437)]$
A_{19}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.4017)(l_1,-0.4339)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,-0.3384)(l_1,0.2896)]$
A_{20}	$[(l_1,0.1787),(l_1,-0.2608)]$	$[(l_1,0.4017)(l_1,-0.4339)]$	$[(l_1,0.3282)(l_1,-0.3711)]$	$[(l_1,-0.3384)(l_1,0.2896)]$

A	C_5	C_6	C_7	C_8
A_1	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_2	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_3	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_4	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_5	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,-0.1648),(l_1,0.0315)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_6	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,-0.1648),(l_1,0.0315)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_7	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,-0.3981),(l_1,0.3648)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_8	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_9	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,-0.1648),(l_1,0.0315)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{10}	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{11}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,-0.1929),(l_1,0.1798)]$
A_{12}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,-0.2315),(l_1,0.1981)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,-0.1929),(l_1,0.1798)]$
A_{13}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{14}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,-0.2315),(l_1,0.1981)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{15}	$[(l_1,-0.1136),(l_1,0.1010)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.0176),(l_1,-0.0291)]$	$[(l_1,-0.1929),(l_1,0.1798)]$
A_{16}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.1842),(l_1,-0.1958)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{17}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.1842),(l_1,-0.1958)]$	$[(l_1,0.1404),(l_1,-0.1535)]$
A_{18}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,-0.3158),(l_1,0.3042)]$	$[(l_1,-0.1929),(l_1,0.1798)]$
A_{19}	$[(l_2,-0.4470),(l_0,0.4343)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,0.1842),(l_1,-0.1958)]$	$[(l_1,-0.1929),(l_1,0.1798)]$
A_{20}	$[(l_1,0.2197),(l_1,-0.2323)]$	$[(l_1,0.1019),(l_1,-0.1352)]$	$[(l_1,-0.1491),(l_1,0.1376)]$	$[(l_1,-0.1929),(l_1,0.1798)]$

A	C_9	C_{10}	C_{11}
A_1	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_2	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_3	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_4	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_5	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_6	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_7	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_0,0.4751),(l_1,0.4523)]$
A_8	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,-0.1916),(l_1,0.1189)]$
A_9	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{10}	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,0.2807),(l_1,-0.2858)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{11}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{12}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{13}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{14}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{15}	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{16}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{17}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{18}	$[(l_1,0.2414),(l_1,-0.2499)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_0,0.4751),(l_1,0.4523)]$
A_{19}	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$
A_{20}	$[(l_1,-0.0920),(l_1,0.0834)]$	$[(l_1,-0.0527),(l_1,0.0475)]$	$[(l_1,0.1418),(l_1,-0.2144)]$

constructing the 2-tuple linguistic Pythagorean fuzzy decision matrix. The data in Table 9 is transformed into its equivalent 2TLPFSs using the transformation provided in Table 10.

The 2 TLPF decision matrix can be seen in Table 11.

After completing the previous step, it was determined that normalization of the evaluation matrix was unnecessary since all the values represented are positively evaluated, and therefore, no normalization is required. The subsequent stage involved establishing the BAA matrix, as presented in Table 12.

Subsequently, the next step involved computing the 2 TLPF distance matrix, which was followed by calculating the distance of each alternative from the BAA matrix. The distances of each alternative from the BAA matrix are provided in Table 13.

The next step involves determining the final scores and ranking the alternatives based on their score values, from high to low, as shown in Table 14.

Table 14
Final score and ranking.

A	Total Distance	Score	Rank
A_1	$[(l_1, 0.0739), (l_1, -0.1130)]$	0.0611	7
A_2	$[(l_1, 0.0739), (l_1, -0.1130)]$	0.0611	7
A_3	$[(l_1, 0.0739), (l_1, -0.1130)]$	0.0611	7
A_4	$[(l_1, 0.0739), (l_1, -0.1130)]$	0.0611	7
A_5	$[(l_1, 0.0210), (l_1, -0.0589)]$	0.0261	17
A_6	$[(l_1, 0.0565), (l_1, -0.0937)]$	0.0491	13
A_7	$[(l_1, -0.0927), (l_1, 0.0641)]$	−0.0515	20
A_8	$[(l_1, -0.0305), (l_1, -0.0040)]$	−0.0087	19
A_9	$[(l_1, 0.0423), (l_1, -0.0813)]$	0.0404	16
A_{10}	$[(l_1, 0.1113), (l_1, -0.1497)]$	0.0854	5
A_{11}	$[(l_1, 0.1321), (l_1, -0.1698)]$	0.0987	3
A_{12}	$[(l_1, 0.1278), (l_1, -0.1664)]$	0.0962	4
A_{13}	$[(l_1, 0.1794), (l_1, -0.2166)]$	0.1296	1
A_{14}	$[(l_1, 0.1567), (l_1, -0.1943)]$	0.1148	2
A_{15}	$[(l_1, 0.0739), (l_1, -0.1130)]$	0.0564	11
A_{16}	$[(l_1, 0.0660), (l_1, -0.1068)]$	0.0481	14
A_{17}	$[(l_1, 0.0584), (l_1, -0.0880)]$	0.0481	14
A_{18}	$[(l_1, -0.0145), (l_1, -0.0157)]$	0.0004	18
A_{19}	$[(l_1, 0.0571), (l_1, -0.0977)]$	0.0506	12
A_{20}	$[(l_1, 0.073942), (l_1, -0.1145)]$	0.0617	6

Table 15
Sensitivity analysis generated weights.

Criteria (Level 1)		Criteria (Level 2)	Criteria (Level 3)	Weight
Performance (C_1)	0.41	Energy performance ($C_{1.1}$)		0.1020
		The flexibility of the	0.0440	0.0632
		system ($C_{1.2}$)	0.0440	0.0632
		Climate Resilience ($C_{1.3}$)	0.0390	0.0561
			0.0390	0.0561
		Building Type ($C_{1.4}$)		0.0600
		Technology Readiness level ($C_{1.5}$)		0.0822
Technical (C_2)	0.59	Possibility to reverse the machine. ($C_{2.1}$)		0.1475
		Possibility to recover heat at the condenser. ($C_{2.2}$)		0.1475
		Possibility to make passive cooling. ($C_{2.3}$)		0.1475
		System Capacity Range ($C_{2.4}$)		0.1475

Table 16
Sensitivity results using inverted weights.

A	Total distance	Score	New Weights-based Rank	Original Weights-based Rank
A_1	$[(l_1, 0.0639), (l_1, -0.0998)]$	0.0536	9	7
A_2	$[(l_1, 0.0639), (l_1, -0.0998)]$	0.0536	9	7
A_3	$[(l_1, 0.0639), (l_1, -0.0998)]$	0.0536	9	7
A_4	$[(l_1, 0.0639), (l_1, -0.0998)]$	0.0536	9	7
A_5	$[(l_1, 0.0270), (l_1, -0.0620)]$	0.0292	17	17
A_6	$[(l_1, 0.0774), (l_1, -0.1115)]$	0.0619	6	13
A_7	$[(l_1, -0.0941), (l_1, 0.0706)]$	−0.0543	20	20
A_8	$[(l_1, -0.0336), (l_1, 0.0024)]$	−0.0118	18	19
A_9	$[(l_1, 0.0418), (l_1, -0.0776)]$	0.0391	13	16
A_{10}	$[(l_1, 0.1160), (l_1, -0.1511)]$	0.0875	5	5
A_{11}	$[(l_1, 0.1328), (l_1, -0.1674)]$	0.0983	3	3
A_{12}	$[(l_1, 0.1299), (l_1, -0.1650)]$	0.0966	4	4
A_{13}	$[(l_1, 0.1867), (l_1, -0.2203)]$	0.1334	1	1
A_{14}	$[(l_1, 0.1711), (l_1, -0.2049)]$	0.1232	2	2
A_{15}	$[(l_1, 0.0348), (l_1, -0.0723)]$	0.0350	15	11
A_{16}	$[(l_1, 0.0787), (l_1, -0.1076)]$	0.0612	7	14
A_{17}	$[(l_1, 0.0787), (l_1, -0.1076)]$	0.0612	7	14
A_{18}	$[(l_1, -0.0361), (l_1, 0.0113)]$	−0.0156	19	18
A_{19}	$[(l_1, 0.0284), (l_1, -0.0658)]$	0.0308	16	12
A_{20}	$[(l_1, 0.0407), (l_1, -0.0779)]$	0.0388	14	6

As seen from Table 14, when the ranking of alternatives in this research (ACs) is performed, it can be seen that out of the n = 20 alternatives presented, the first was A_{13} ranked with the highest score value (0.1296), followed by $A_{14} > A_{11} > A_{12}$ with score values (0.1148, 0.0987, and 0.0962) for the 2nd, 3rd, and 4th ranks, respectively. The worst-performing alternative A_7 was assigned a score value of *-0.0515*. Some interesting patterns are observed, including alternatives that maintained similar scores and ranking (7th rank), including A_1, A_2, A_3, and A_4.

The evaluation results have significant policy implications, as they highlight the effectiveness and potential benefits of implementing the best alternatives. Policymakers should prioritize the implementation of these alternatives, considering their promising performance. Additionally, poor-performing alternatives should be carefully assessed, and alternative approaches should be considered to address their shortcomings. Upon the completion of the final ranking results, robustness checks must be applied, and the results in the ranking and criteria weights must undergo an evaluation process, as discussed in the following section.

5.3. Results evaluation

One of the most well-established methods for assessing and verifying the robustness of emerging MCDM methods is sensitivity analysis, which has been extensively used in MCDM research. This method takes the criteria weights into account and experiments with changing them under different settings to see how it affects the rankings. Several scenarios are considered when performing a sensitivity analysis, which can be done in several different ways before making the weight adjustments, as seen for a total of 11 criteria in Table 15.

The philosophy for sensitivity analysis yielded a novel set of weights, as reported in Table 15. The new set of weights was generated by switching the main criteria weights, where C_1's main criteria weight was assigned to C_2 criteria and vice versa. After that, FWZIC weights for ($C_{1.1}$–$C_{1.5}$) were normalized by multiplying them with the new weight of the C_1 main criteria, resulting in the new weight. The other philosophy for the remaining criteria ($C_{2.1}$–$C_{2.4}$) was the same as previously discussed, where the C_2 main criteria were equally distributed over their subcriteria, which resulted in the final set of weights. These updated weights are used to determine rankings, as given in Table 16.

Table 16 presents the new rank based on the weights generated by sensitivity analysis versus the original rank. It is seen that some changes are apparent, including the first 4 alternatives (A_1, A_2, A_3, and A_4), whose rank changes from being 7th in the original to 9th with the introduction of the new weights. This can be observed not only in these cases, but more apparent changes are also clear. A good example includes some drastic rank changes; for instance, alternative went from being the 13th-ranked alternative to being the 6th, and that presented more than *50%* changes in the two ranks combined. It is clear that weight changes have their effect on the overall rank, whether these changes are slight or drastic. At the same time, some alternatives maintained their rank over the two settings. This includes (A_{13}, A_{14}, A_{11}, A_{12}, A_{10}, A_5, and A_7) where the rank was maintained; this shows these alternatives' dominancy, which also presents the fact that weight changes can affect some cases and might not affect others. At the same time, weight importance cannot be overlooked, and it is quite vital to any decision-making content. With the introduction of more weight scenarios in the future, these alternatives are more likely to be affected and changed.

6. Policy implication

There are wide-ranging policy implications for the government, businesses, and households associated with the evaluation and selection of integrated ACs utilising the proposed MCDM model. Their decisions also have varying effects on the economy and the environment.

The policy implications for the government revolve around encouraging and incentivizing the widespread use of these systems, as well as promoting sustainable building practices. Government policy can be informed by the findings of the proposed evaluation to promote investment and adoption of such systems by manufacturers and households. Financial incentives can encourage producers to manufacture these systems and motivate homeowners to install them, thus fostering sustainable building practices. By taking these measures, the government can encourage sector growth, facilitate the transition to greener cooling technologies, and promote sustainable building practices. Recognizing the market potential and competitive advantage of integrated ACs has significant policy consequences for manufacturers. The findings of the evaluation may encourage manufacturers to continue developing and mass-producing these systems. This, in turn, can enhance their competitiveness, provide access to a growing market, contribute to economic growth, and promote sustainable building practices. To encourage the adoption of integrated ACs for sustainable building practices in private residences, policymakers will need to disseminate relevant information, raise public awareness, and provide incentives. The evaluation findings can educate homeowners about the advantages of these systems, including reduced energy consumption, improved comfort, and minimized environmental impact. The government can promote the usage of such systems in sustainable building practices by offering information to households about their benefits and providing financial aid in the form of low-interest loans or grants. By increasing access to these systems in homes, the policy can encourage energy savings, reduce electricity use, lower utility bills, and promote sustainable building practices.

The policy consequences are interconnected with the effects on the economy and the environment. The implementation of evaluated ACs can stimulate the manufacturing sector, create new jobs, and fuel innovation, thereby contributing to economic growth. It can also result in energy savings, reducing overall electricity consumption and utility bills for homes and businesses. Conventional cooling technologies often use refrigerants that have a significant global warming effect on climate change; however, the adoption of selected systems can help mitigate this impact. By encouraging the use of energy-efficient and environmentally friendly cooling systems, the policy can contribute to achieving sustainability goals.

7. Conclusion

Using a novel MCDM model, this study aimed to address the evaluation issues of ACs. Two approaches, FWZIC and modified MABAC, were used to evaluate the available ACs and weight the assessment criteria. In order to address the theoretical difficulty of delivering better evaluations in the presence of ambiguities and inconsistencies among DMs, both methods have been developed based on a 2TLPFSs environment. A sensitivity analysis validated the robustness of the proposed model. However, there are some limitations to the study from the perspective of ACs and MCDM research. As there is little information on the topic of cooling systems' resistance to heatwaves and power outages, this posed a challenge for the former, particularly since each system is also being discussed under unique boundary conditions. From an MCDM perspective, the relative contribution or weight of each expert was not obtained when they were asked to provide their knowledge or opinions. This lack of information could have an impact on the final criteria weights and alternative selection in the case study being discussed, as well as in any potential future cases. One of our future studies will address this issue by proposing a new mechanism for assigning specific weights to each expert, which can be utilized in determining the criteria weights. Finally, we also aim to explore the potential of combining new fuzzy sets and precise fuzzy operators with the proposed MCDM methods.

CRediT authorship contribution statement

O.S. Albahri: Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **A.H. Alamoodi:** Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Muhammet Deveci:** Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **A.S. Albahri:** Supervision, Validation, Writing – review & editing. **Moamin A. Mahmoud:** Supervision, Writing – review & editing. **Iman Mohamad Sharaf:** Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **D'Maris Coffman:** Supervision, Validation, Writing – original draft, Writing – review & editing.

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

The data that has been used is confidential.

Acknowledgement

This work was supported by Tenaga Nasional Berhad (TNB) and UNITEN through the BOLD Refresh Postdoctoral Fellowships under the project code of J510050002-IC-6 BOLDREFRESH2025-Center of Excellence.

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