Renewable Energy 256 (2026) 124538

Contents lists available at ScienceDirect

Renewable Energy

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

Integration of recursive feature elimination in renewable energy sources with evaluation based on relative utility and nonlinear standardization

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ARTICLE INFO

Keywords:
Linear diophantine fuzzy set
LOPCOW
ERUNS
RFE
Renewable energy source selection
Optimization

ABSTRACT

The transition to renewable energy (RE) is essential for sustainable development and energy security, especially in rapidly urbanized areas. This research presents a new decision-making framework designed to identify the most effective renewable energy sources for Shenzhen, China. The framework employs Recursive Feature Elimination (RFE) to condense 14 initial criteria to the 5 most significant factors, thereby improving evaluation efficiency while maintaining analytical accuracy. This method integrates a logarithmic percentage change-driven objective weighting technique (LOPCOW) with evaluation based on relative utility and nonlinear standardization (ERUNS), which is subsequently enhanced through the application of the linear diophantine fuzzy soft-max average (LiDFSMA) operator. This hybrid model addresses uncertainty in multi-criteria decision making (MCDM) by employing advanced weighting and aggregation techniques. Empirical results indicate that solar thermal power is the most effective alternative for Shenzhen, due to its reliable power generation capacity and suitability for areas with direct sunlight. Pseudocode inclusion promotes transparency and facilitates replicability. The proposed method provides a reliable, objective, and flexible instrument for RE planning, significantly influencing the acceleration of sustainable energy adoption in urban environments.

1. Introduction

As global concerns about climate change grow, communities throughout the world are increasingly understanding the importance of transitioning to RE sources. This change seeks not only to decrease the negative consequences of greenhouse gas emissions but also to promote sustainable urban growth and energy security for future generations. In this context, an urbanized city is launching a strategic endeavour to determine the best RE source to satisfy its future electricity needs. To provide a complete and rigorous examination, alternatives will be evaluated based on important criteria. These criteria and alternatives cover a wide range of factors necessary for making a knowledgeable and balanced decision. Decision-makers often need to make judgements under uncertainty in a complex, interrelated world with conflicting criteria. Real-world problems are usually multi-criteria problems, and traditional decision-making methods that consider one criterion, such as cost or performance, are inadequate. MCDM is an approach to evaluating and ranking competing alternatives when applied to multiple criteria related to decision-making appraisals. These methods are intended to guide the decision-maker in exploring the complexity, not to automate the decision process. They can provide a framework to assist in the analysis of a wide range of complex problems related to the evaluation and selection of alternatives based on multiple, often conflicting, criteria and can promote objective, consistent, transparent, and auditable decision-making. Although they can be quite useful when apologies need to be devised based on a comprehensive assessment of quantitative and qualitative aspects.

Zadeh introduced the concept of FS as an alternative to precise numbers or linguistic concepts [1]. Atanassov introduced IFS [2], providing a geometric interpretation of IFS and logic, which offers foundational insights into their structure beyond algebraic formulations [3]. This research enhances comprehension of IFS, which is beneficial for advanced fuzzy modelling applications. Yager and Abbasov [4] introduced PF subsets and associated them with $\Pi - i$ complex numbers. To enhance decision-making in the presence of uncertainty, they implemented this framework. Yager [5] also introduced PFS and compared it to IFS. Using the Pythagorean theorem, the study underscored the significance of negation. Yager proposed aggregation operators for PFS in MCDM [6]. The paper demonstrated the increased flexibility that these sets provide in managing uncertainty. Yager proposed q-ROFS, which combines IFS and PFS [7]. Mardani et al. [8] developed a hierarchical

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https://doi.org/10.1016/j.renene.2025.124538
Received 29 March 2025; Received in revised form 6 August 2025; Accepted 28 September 2025
Available online 6 October 2025

Table 1
A comprehensive research work on LOPCOW.

Authors	Year	Weighting method	Application
Bektas, S. [21]	2022	LOPCOW-EDAS	Evaluate the performance of the Turkish insurance sector.
Ecer & Pamucar [22]	2022	LOPCOW-Dombi	Banks in poor countries are assessed for their sustainability.
Altıntaş [23]	2023	LOPCOW-CRADIS	Analysing G7 countries' prosperity performance.
Ecer et al. [24]	2023	LOPCOW-CoCoSo	Sustainability assessment of micro-mobility systems in urban transportation.
Putra et al. [25]	2024	LOPCOW-MARCOS	Selection of the most distinguished teacher.
Ulutaş et al. [26]	2024	LOPCOW-PSI-G	Evaluation of 3PL service providers for automotive businesses.
Korucuk et al. [27]	2024	LOPCOW-RAFSI	Humanitarian relief organizations choose warehouse locations.
Rong et al. [28]	2024	LOPCOW-ARAS	Risk evaluation for R&D projects in industrial robot offline programming systems.

framework integrating fuzzy MCDM approaches to evaluate and rank key energy-saving technologies and solutions in major Iranian hotels. Banadkouki [9] developed a hybrid approach using the Entropy Weight Method and fuzzy TOPSIS to select strategies for improving energy efficiency in the ceramic tile industry in Iran. Riaz et al. [10] used a q-rung orthopair fuzzy MULTIMOORA technique to increase energy efficiency in low-income families in Pakistan, evaluating four alternatives based on eight criteria. Kabak et al. [11] used a fuzzy MCDM approach to evaluate and categorize building energy performance, with an emphasis on the BEP-TR methodology in Turkey. Dinesh and Santhosh Kumar [12] created the NF-SSOA protocol, which combines neuro-fuzzy clustering and sparrow search optimization to improve energy efficiency and security in wireless sensor networks. Oladipo et al. [13] created an improved PSO-ANFIS model for estimating energy usage in university housing, which outperformed existing techniques. Biswas et al. [14] developed the ERUNS approach for evaluating business performance in the energy sector within an EESG framework, resulting in consistent and reliable rankings. The EECHIGWO algorithm was created by Reddy et al. [15] to improve the energy efficiency and network lifetime in wireless sensor networks by selecting better cluster heads. A study by Si et al. [16] used a fuzzy-AHP method to look at how energy-efficient different post-treatment technologies were for coal-fired units. They found that a new high-temperature precipitator control route was particularly useful. Varmaghani et al. [17] came up with the DMTC approach, which uses fog computing and fuzzy MADM to make dynamic wireless sensor networks use less energy and last longer. Simic et al. [18] presents a neutrosophic MCDM model, T2NN-LOPCOW-ARAS, for putting Industry 4.0-based material handling technologies at the top of smart and environmentally friendly warehouse management systems. Chatterjee and Chakraborty [19] looked at how ten different objective weighting approaches affected TOPSIS-based parametric optimization of non-traditional machining processes. They discovered that the ranks of the experiment trials were the same for all ten approaches.

Riaz and Hashmi [20] proposed LiDFS, a generic approach that includes IFS, PFS, and q-ROFS. LiDFS is a revolutionary methodology for assessing uncertain decision-making processes, improving computing efficiency, and resolving complicated real-world scenarios using reference parameters. In energy efficiency assessments, fuzzy MCDM techniques are used to analyse numerous criteria that include both quantitative and qualitative elements, converting expert opinions into measurable data. Fuzzy logic is used to address the subjective and fluctuating character of variables like environmental effects and societal acceptance, resulting in a more balanced and nuanced judgment. The proposed method improves decision-making by including uncertainty and offering a full assessment framework. Many researchers used the LOPCOW approach to calculate objective weights in MCDM studies. Table 1 shows how this strategy has been effective in numerous applications.

Table 2 shows a summary of current empirical research applying several fuzzy MCDM ways in RE decision-making, highlighting the methodologies and particular applications in RE.

Table 3 presents a detailed compilation of essential symbols and acronyms used in the study, facilitating reader understanding and maintaining consistency in terminology.

Fig. 1 depicts significant themes and links between renewable energy and environmental sciences. The clusters illustrate trends and relationships between different renewable energy technologies. These insights help academics and policymakers identify thematic areas and multidisciplinary connections, facilitating the formulation of tailored plans for sustainable energy and environmental management. It visualizes research patterns, allowing for more informed decision-making and stimulating innovation in the face of global environmental concerns. Finally, the analysis emphasizes the significance of integrating environmental sustainability, social equality, and technical advancement to effectively address current ecological and energy concerns.

This research advances the existing literature by establishing a reproducible and scalable decision-support framework that combines both objective and subjective elements through the application of advanced MCDM techniques. The proposed method differs from prior research by integrating RFE for dynamic criterion selection, LOPCOW–ERUNS for robust evaluation, and the LiDFSMA operator for aggregating expert input in fuzzy environments, rather than relying on fixed criteria or limited uncertainty handling. The framework undergoes testing in a real-world case study in Shenzhen, and its transparent design through pseudocode facilitates generalization across urban RE planning scenarios. These innovations set a new methodological standard for decision-making in policy-relevant RE contexts.

1.1. Literature review about RFE

The RFE is a versatile and powerful problem-solving technique used to decrease the amount of features in data. It is widely applied in several fields. Simic et al. [34] propose a decision support system for locating disinfection facilities for hazardous healthcare waste during COVID-19. The system uses a multi-stage model integrating the random forest RFE algorithm, ITARA, and MARCOS methods in an FF environment and is robustly demonstrated through a case study in Istanbul. Chen and Jeong [35] introduce an EnRFE method that enhances performance by retaining weak features that, when combined with others, increase classification accuracy for small training sample problems. Yan and Zhang [36] introduce an enhanced version of the SVM-RFE algorithm. This algorithm specifically tackles the problem of correlation bias in feature selection for gas sensor data. Their empirical findings demonstrate that the novel algorithm improves classification accuracy and surpasses the original SVM-RFE and other conventional techniques. Chen et al. [37] introduce WERFE, a gene selection algorithm that combines various methods in an RFE framework to provide a concise and highly informative subset of genes. This algorithm achieves outstanding performance in classifying microarray data. Lin et al. [38] propose SVM-RFE-OA, a feature selection technique that enhances SVM-RFE by considering classification accuracy and average overlapping ratio. These methods demonstrate improved stability and accuracy in bioinformatics applications.

- The urgent need to address global climate change through the switch to RE sources serves as the study's driving force. This transition aims to cut greenhouse gas emissions while also promoting sustainable urban expansion and energy security for future generations.

Table 2
Empirical studies on fuzzy MCDM Applications in RE.

Author(s)	Year	Methodology	Application
Sekeroglu[29]	2024	GIS-based spatial modelling with fuzzy operators	Selection of sites for biomass–solar hybrid RE installations in Türkiye
Jameel et al. [30]	2024	Entropy-SWARA with modified CoCoSo	Evaluation of RE sources for sustainable development in industry 4.0
Husain et al. [31]	2024	Entropy-CRITIC with different MCDM methods	Evaluating RE sources in India for efficient energy development
Shen et al. [32]	2025	Collaborative filtering with MORAN ranking method	Selection of strategies to mitigate the impacts of climate change on RE performance
Rocha et al. [33]	2025	Fuzzy analytical hierarchy process	Assessment of RE sources in Colombia according to regional capabilities

Table 3
List of acronyms.

Term	Abbreviation
Renewable energy	RE
Recursive feature elimination	RFE
Fuzzy Set	FS
Linear Diophantine fuzzy set	LiDFS
Linear Diophantine fuzzy soft-max average	LiDFSMA
Support vector machine	SVM
Multi-criteria decision-making	MCDM
Logarithmic percentage change-driven objective weighting	LOPCOW
Evaluation based on relative utility and nonlinear standardization	ERUNS
Indifference threshold-based attribute ratio analysis	ITARA
Measurement of alternatives and ranking according to the compromise solution	MARCOS
Intuitionistic fuzzy set	IFS
q-Rung fuzzy sets	q-RFSs
Pythagorean fuzzy set	PFS
Aggregation operator	AO
Decision-maker	$\mathfrak{DM}$

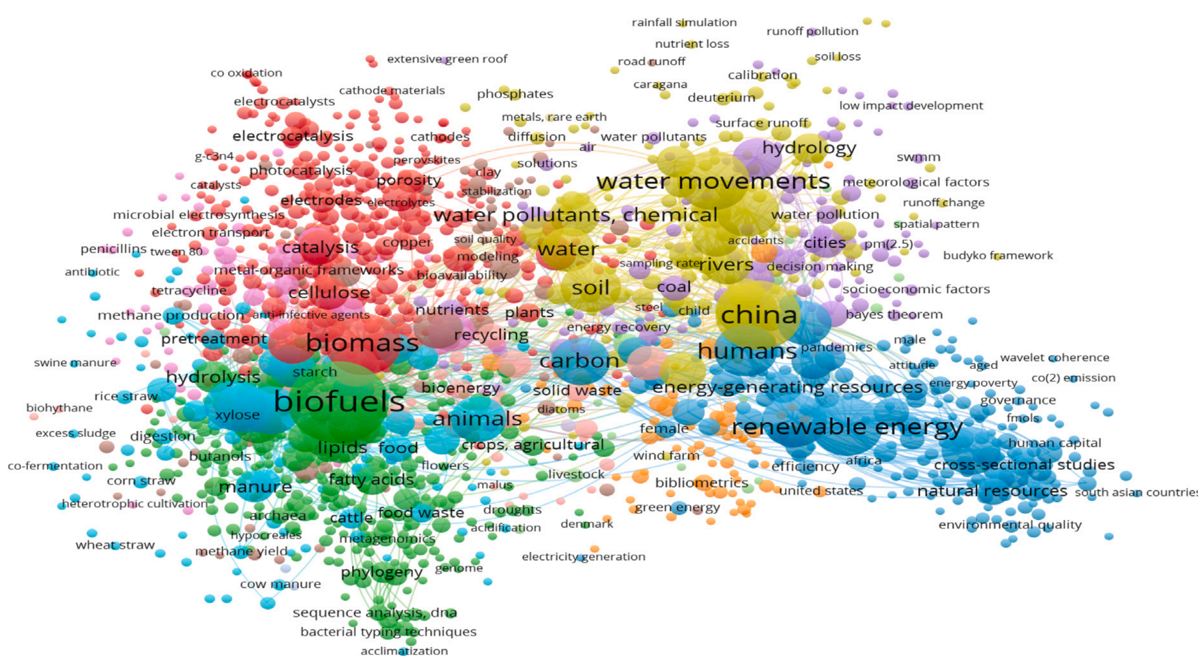

Fig. 1. Visualization of keyword co-occurrence in renewable energy and environmental sciences.

- The uses LiDFS to handle the inherent ambiguity and complexity of decision-making processes more efficiently. Using the LiDFSMA operator improves the aggregation of decision-makers information, allowing for more precise and fair evaluations of RE options.
- The paper aims to advance the use of fuzzy MCDM methodologies, including quantitative and qualitative criteria, and address the ambiguity inherent in decision-making processes. This entails taking expert opinions and translating them into quantifiable facts.

- Shenzhen serves as a pertinent case study due to its unique combination of significant energy demand, rapid urbanization, and commitment to sustainability. The city's ambitious RE projects provide a framework for evaluating and substantiating the proposed technique, addressing the challenges of aligning urban development with environmental conservation.
- The paper presents a novel LOPCOW-ERUNS technique that is combined with the LiDFSMA operator for aggregation. This technique seeks to improve decision-making precision and reliability by combining advanced objective weighting methods and complex aggregation operators, resulting in a comprehensive framework for evaluating RE choices.

1.2. Motivation and objectives

The increasing need for global climate change has increased the necessity for efficient, data-informed frameworks to facilitate the transition to RE. This transition is essential for reducing greenhouse gas emissions, improving energy security, and facilitating sustainable urban development. RE decision-making is complex, influenced by conflicting evaluation criteria, uncertainty in expert input, and sensitivity to regional factors. This study addresses the necessity of overcoming decision-making challenges, and it also examines the policy-level issue of systematically prioritizing RE alternatives in rapidly urbanizing areas, such as Shenzhen, China. Existing MCDM models have contributed significantly; however, they frequently encounter challenges related to data dimensionality, fuzzy uncertainty, and aggregation transparency. This study presents a hybrid decision-making framework designed to address existing gaps. It incorporates three essential components: RFE for the selection of impactful evaluation criteria, the LOPCOW–ERUNS technique for objective weighting and evaluation, and the LiDFSMA operator for aggregating expert input under conditions of uncertainty. Then it facilitates implementation via the MATLAB code, promoting transparency and adaptability across various policy contexts. Shenzhen is selected as the case study because of its significant energy demand, swift urbanization, and dedication to RE advancement. This serves as an optimal environment for validating the proposed method. The model, while applied to Shenzhen, possesses a modular and generalizable structure, enabling adaptation to other urban regions worldwide. The key objectives of this study are:

- To create a comprehensive MCDM model that incorporates both qualitative and quantitative factors.
- Incorporate expert opinions into a systematic and replicable decision-making process.
- To enhance MCDM methodology by refining aggregation techniques in the context of uncertainty.
- To provide a practical and transparent resource for policymakers engaged in RE planning.

1.3. Structure of the paper

This study presents the LOPCOW-ERUNS approach, augmented by the LiDFSWA aggregation operator, to efficiently identify the optimal alternative from a set of options. Section 1 commences with an introduction and a thorough literature review, situating our research within the current academic discourse and identifying the gaps that our methodology seeks to fill. Section 2 outlines the fundamental concepts and terminology necessary for comprehending the methodology, thereby preparing readers for subsequent sections. Section 3 presents the proposed LOPCOW-ERUNS framework, which incorporates the LiDFSWA aggregation operator, and illustrates its application via a case study on RE alternatives in Shenzhen. This section presents a systematic implementation guide and demonstrates the application of our approach for evaluating various energy sources, including solar, wind, and biomass, within the framework of Shenzhen's energy strategy. This case study demonstrates the method's practical utility in real-world decision-making contexts. Section 4 presents a sensitivity analysis to evaluate the robustness of the proposed method across different conditions, comparing its performance with other existing approaches to demonstrate the advantages and superior outcomes of the LOPCOW-ERUNS method. Section 5 concludes the paper by summarizing key findings, discussing the significance of the proposed technique, and suggesting areas for future research, while reflecting on the broader contributions of this work to the field.

2. Preliminaries

Definition 2.1 (*[1]*)**.** A fuzzy set $\mathfrak{FS}$ within a universal set $\mathfrak{X}$ can be described as follows:

$$\mathfrak{FS} = \{(\wp, \mathfrak{T}_F(\wp)) \mid \wp \in \mathfrak{X}\} \tag{1}$$

Here, $\mathfrak{T}_F$ is known as the membership function, which maps elements from the universal set $\mathfrak{X}$ to the interval $[0,1]$. The value $\mathfrak{T}_F(\wp)$ represents the membership degree of the element $\wp$ in the fuzzy set F.

Definition 2.2 (*[2]*)**.** An IFS A on a universal set $\mathfrak{X}$ is defined as:

$$\mathfrak{A} = \left\{\left(\wp, \mathfrak{T}_{\mathfrak{A}}(\wp), \mathfrak{F}_{\mathfrak{A}}(\wp)\right) \mid \wp \in \mathfrak{X}\right\}$$

Where $\mathfrak{T}_{\mathfrak{A}}$ and $\mathfrak{F}_{\mathfrak{A}}$ denote the membership and non-membership grades, respectively. These are the mappings from $\mathfrak{X}$ to $[0,1]$ with $0 \le \mathfrak{T}_{\mathfrak{A}}(\wp), \mathfrak{F}_{\mathfrak{A}}(\wp) \le 1$ and $0 \le \mathfrak{T}_{\mathfrak{A}}(\wp) + \mathfrak{F}_{\mathfrak{A}}(\wp) \le 1$ for all $\wp \in \mathfrak{X}$. The pairs of these functions are denoted by $\mathfrak{A} = \left(\mathfrak{T}_{\mathfrak{A}}, \mathfrak{F}_{\mathfrak{A}}\right)$ and called an intuitionistic fuzzy number (IFN).

Definition 2.3 (*[20]*)**.** Let $\mathfrak{X}$ be a set. A linear diophantine fuzzy set (LiDFS) Ω in $\mathfrak{X}$ is an object of the form:

$$\Omega_\alpha = \left\{\left(\varsigma, (\mathfrak{T}_\alpha(\varsigma), \mathfrak{F}_\alpha(\varsigma)), (\alpha(\varsigma), \beta(\varsigma))\right) : \varsigma \in \mathfrak{X}\right\}$$

where, $\mathfrak{T}_\alpha(\varsigma), \mathfrak{F}_\alpha(\varsigma), \alpha, \beta \in [0,1]$ are membership, non-membership and reference parameters, respectively. These grades satisfy the condition

$$0 \le \alpha\mathfrak{T}_\alpha(\varsigma) + \beta\mathfrak{F}_\alpha(\varsigma) \le 1 \ \forall \varsigma \in \mathfrak{X}$$

with $0 \le \alpha + \beta \le 1$. The hesitancy part can be evaluated as $\xi\pi_\alpha = 1-(\alpha\mathfrak{T}_\alpha(\varsigma)+\beta\mathfrak{F}_\alpha(\varsigma))$, where ξ is the reference parameter related to degree of hesitancy.

Definition 2.4 (*[20]*)**.** A number of the form $\Lambda = ((\mathfrak{T}_\alpha, \mathfrak{F}_\alpha), (\alpha, \beta))$ is called a linear Diophantine fuzzy number (LDFN) with $0 \le \alpha\mathfrak{T}_\alpha + \beta\mathfrak{F}_\alpha \le 1$ and $0 \le \alpha + \beta \le 1$.

Definition 2.5 (*[20]*)**.** A LiDFS in $\mathfrak{X}$ of the form ${}^1\Omega_\alpha = \{(\varsigma, (1,0), (1,0)) : \varsigma \in \mathfrak{X}\}$ is called absolute LiDFS. An LiDFS in $\mathfrak{X}$ of the form ${}^0\Omega_\alpha = \{(\varsigma, (0,1), (0,1)) : \varsigma \in \mathfrak{X}\}$ is called an empty or null LiDFS.

Definition 2.6 (*[20]*)**.** Let $L = (\langle\mathfrak{T}_L, \mathfrak{F}_L\rangle, \langle\alpha_L, \beta_L\rangle)$ be a LiDFN, then score function $Sc(L)$ can be defined by the mapping $Sc(L) : LiDFN(L) \to [0,1]$ and given by

$$Sc(L) = \frac{1}{2}\left[\frac{(\mathfrak{T}_L - \mathfrak{F}_L + 1)}{2} + \frac{(\alpha_L - \beta_L + 1)}{2}\right] \tag{2}$$

Definition 2.7 (*[20]*)**.** Let $L = (\langle\mathfrak{T}_L, \mathfrak{F}_L\rangle, \langle\alpha_L, \beta_L\rangle)$ be a LiDFN, then accuracy function can be defined by the mapping $\psi : LiDFN(\beth) \to [0,1]$ and given as

$$\psi(L) = \frac{1}{2}\left[\left(\frac{\mathfrak{T}_L + \mathfrak{F}_L}{2}\right) + (\alpha_L + \beta_L)\right]$$

$$
\begin{array}{cc}
 & \\
\mathfrak{DM}_1 & \mathfrak{Al}_1 \\
 & \\
 & \mathfrak{Al}_m \\
\mathfrak{DM}_2 & \mathfrak{Al}_1 \\
 & \\
 & \mathfrak{Al}_m \\
\mathfrak{DM}_p & \mathfrak{Al}_1 \\
 & \\
 & \mathfrak{Al}_m
\end{array}
\begin{array}{c}
\begin{array}{cccc} \quad\mathfrak{Cr}_1\quad & \quad\mathfrak{Cr}_2\quad & & \quad\mathfrak{Cr}_n\quad \end{array} \\
\begin{bmatrix}
(\langle \mathfrak{T}^1_{11}, \mathfrak{F}^1_{11}\rangle, \langle \alpha^1_{11}, \beta^1_{11}\rangle) & (\langle \mathfrak{T}^1_{12}, \mathfrak{F}^1_{12}\rangle, \langle \alpha^1_{12}, \beta^1_{12}\rangle) & \cdots & (\langle \mathfrak{T}^1_{1n}, \mathfrak{F}^1_{1n}\rangle, \langle \alpha^1_{1n}, \beta^1_{1n}\rangle) \\
\vdots & \vdots & \ddots & \vdots \\
(\langle \mathfrak{T}^1_{m1}, \mathfrak{F}^1_{m1}\rangle, \langle \alpha^1_{m1}, \beta^1_{m1}\rangle) & (\langle \mathfrak{T}^1_{m2}, \mathfrak{F}^1_{m2}\rangle, \langle \alpha^1_{m2}, \beta^1_{m2}\rangle) & \cdots & (\langle \mathfrak{T}^1_{mn}, \mathfrak{F}^1_{mn}\rangle, \langle \alpha^1_{mn}, \beta^1_{mn}\rangle) \\
(\langle \mathfrak{T}^2_{11}, \mathfrak{F}^2_{11}\rangle, \langle \alpha^2_{11}, \beta^2_{11}\rangle) & (\langle \mathfrak{T}^2_{12}, \mathfrak{F}^2_{12}\rangle, \langle \alpha^2_{12}, \beta^2_{12}\rangle) & \cdots & (\langle \mathfrak{T}^2_{1n}, \mathfrak{F}^2_{1n}\rangle, \langle \alpha^2_{1n}, \beta^2_{1n}\rangle) \\
\vdots & \vdots & \ddots & \vdots \\
(\langle \mathfrak{T}^2_{m1}, \mathfrak{F}^2_{m1}\rangle, \langle \alpha^2_{m1}, \beta^2_{m1}\rangle) & (\langle \mathfrak{T}^2_{m2}, \mathfrak{F}^2_{m2}\rangle, \langle \alpha^2_{m2}, \beta^2_{m2}\rangle) & \cdots & (\langle \mathfrak{T}^2_{mn}, \mathfrak{F}^2_{mn}\rangle, \langle \alpha^2_{mn}, \beta^2_{mn}\rangle) \\
(\langle \mathfrak{T}^p_{11}, \mathfrak{F}^p_{11}\rangle, \langle \alpha^p_{11}, \beta^p_{11}\rangle) & (\langle \mathfrak{T}^p_{12}, \mathfrak{F}^p_{12}\rangle, \langle \alpha^p_{12}, \beta^p_{12}\rangle) & \cdots & (\langle \mathfrak{T}^p_{1n}, \mathfrak{F}^p_{1n}\rangle, \langle \alpha^p_{1n}, \beta^p_{1n}\rangle) \\
\vdots & \vdots & \ddots & \vdots \\
(\langle \mathfrak{T}^p_{m1}, \mathfrak{F}^p_{m1}\rangle, \langle \alpha^p_{m1}, \beta^p_{m1}\rangle) & (\langle \mathfrak{T}^p_{m2}, \mathfrak{F}^p_{m2}\rangle, \langle \alpha^p_{m2}, \beta^p_{m2}\rangle) & \cdots & (\langle \mathfrak{T}^p_{mn}, \mathfrak{F}^p_{mn}\rangle, \langle \alpha^p_{mn}, \beta^p_{mn}\rangle)
\end{bmatrix}
\end{array}
$$

Box I.

Definition 2.8 ([20]). Let L_1 and L_2 be two LiDFNs, then by using the score function and accuracy function, we have:

(i): If $Sc(L_1) < Sc(L_2)$ then $L_1 < L_2$,

(ii): If $Sc(L_2) < Sc(L_1)$ then $L_2 < L_1$,

(iii): If $Sc(L_2) = Sc(L_1)$ then,

(a): If $\psi(L_1) < \psi(L_2)$ then $L_1 < L_2$,

(b): If $\psi(L_2) < \psi(L_1)$ then $L_2 < L_1$,

(c): If $\psi(L_1) = \psi(L_2)$ then $L_1 = L_2$.

3. Integrated RFE, LOPCOW-ERUNS framework

Step 1: Recursive feature elimination method

Step 1.1: Start with all features, $\mathbf{X} = \{x_1, x_2, \dots, x_n\}$ corresponding to each alternative in the form of LiDFNs. Then set the number of features to select, let us say k.

Step 1.2: Calculate the score values by using Eq. (2) and importance of each feature by using Eq. (3).

$$I_j = \frac{1}{m}\sum_{i=1}^{m} x_j \tag{3}$$

Step 1.3: Calculate the least important feature by using Eq. (4), and eliminate the feature that has the least feature value.

$$I_j^* = min(I_j) \tag{4}$$

Repeat the process until the number of features left in $\mathbf{X}$ is k.

Step 2: Decision makers provide their expert value through a LiDF data set for the selected feature or criteria (see Box I).

Step 3: [39] Calculate the aggregated values by applying the LiDFSMA operator to the assessment information of each decision maker. For this purpose, we use Eq. (5). Assume that $L_\lambda = (\langle \mathfrak{T}, \mathfrak{F}\rangle, \langle \alpha_\lambda, \beta_\lambda\rangle)$ is the assemblage of LiDFNs, we can find LiDFSMA by

$$\mathrm{LiDFSMA}(L_1, L_2, \dots L_n) = \left(\left\langle 1 - \prod_{\lambda=1}^{n}(1-\mathfrak{T})^{\Phi^{\sigma}_{ij}}, \prod_{\lambda=1}^{n}\mathfrak{F}^{\Phi^{\sigma}_{ij}}\right\rangle, \left\langle 1 - \prod_{\lambda=1}^{n}(1-\alpha_\lambda)^{\Phi^{\sigma}_{ij}}, \prod_{\lambda=1}^{n}\beta_\lambda^{\Phi^{\sigma}_{ij}}\right\rangle\right) \tag{5}$$

Where $\Phi^{\sigma,\, l}_{ij} = \dfrac{\exp\left(\frac{T^l_{ij}}{\sigma}\right)}{\sum_{j=1}^{m}\exp\left(\frac{T^l_{ij}}{\sigma}\right)}$ and $T^l_{ij} = \begin{cases} \prod_{k=1}^{j-1} Sc^l_{ik} & j = 2, 3, \dots, m \\ 1 & j = 1 \end{cases}$.

The score value Sc can be found by using Eq. (2).

Step 4: Find the score matrix Sc_{ij} of the aggregated decision matrix by applying Equation (2). Then normalize this matrix using (6)

$$\widetilde{Sc}_{ij} = \begin{cases} \dfrac{Sc_{ij} - Sc_j^-}{Sc_j^+ - Sc_j^-}, & j \in \mathtt{Cr}_b \\ \dfrac{Sc_j^+ - Sc_{ij}}{Sc_j^+ - Sc_j^-}, & j \in \mathtt{Cr}_c \end{cases} \tag{6}$$

Where $Sc_j^+ = \max_i Sc_{ij}, Sc_j^- = \min_i Sc_{ij}, \mathtt{Cr}_b$ and $\mathtt{Cr}_c$ represent the benefit-type and cost-type criteria, respectively. **Step 5:** Obtain the percentage value for the criteria by using Eq. (7).

$$P_j = \left| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m}\widetilde{Sc}^2_{ij}}{m}}}{\sigma} \right) \cdot 100 \right| \tag{7}$$

Where σ is the standard deviation of the performance values of the alternatives under a specific criterion.

Step 6: The weight for the jth criterion is calculated by using Eq. (8).

$$w(Cr_j) = \frac{P_j}{\sum_{j=1}^{n} P_j} \tag{8}$$

Where, $\sum_{j=1}^{n} w(Cr_j) = 1$

3.1. Proposed method: ERUNS

Step 7: The standardization of the elements of the matrix $\mathfrak{X} = [x_{ij}]_{m\times n}$ to the interval $[\lambda, \tau]$ is carried out by using Eq. (9).

$$\mathfrak{T}_{ij} = \left(\frac{x_j^{\min}}{x_{ij}}\right)^3 \tau + \frac{\lambda}{x_j^{\min}} \tag{9}$$

Here, $x_j^{\min} = \min_{1\le i\le m}(x_{ij})$. The values of the interval $[\lambda, \tau]$ depend on the specifics of the decision-making problem and are defined based on the decision-maker's preferences.

Step 8: The criterion is of the max type, the values of $\mathfrak{X}^N = [\mathfrak{T}_{ij}]_{m\times n}$ are modified by applying Eq. (10).

$$\xi_{ij} = \begin{cases} -\mathfrak{T}_{ij} + \max\limits_{1\le i\le m}(\mathfrak{T}_{ij}) + \min\limits_{1\le i\le m}(\mathfrak{T}_{ij}), & j \in \mathtt{Cr}_b \\ \mathfrak{T}_{ij}, & j \in \mathtt{Cr}_c \end{cases} \tag{10}$$

Step 9: The weighted standardized decision matrix is found by using Eq. (11).

$$v_{ij} = \frac{\exp\left(f\left(\xi_{ij}\right)/k\right) w_j}{\sum_{j=1}^{n} \exp\left(f\left(\xi_{ij}\right)/k\right) w_j} \tag{11}$$

where $f\left(\xi_{ij}\right) = \frac{\xi_{ij}}{\sum_{j=1}^{n} \xi_{ij}}, j \in \{1, 2, 3 \dots n\}$.

Step 10: Derive the utility degrees for the ideal and anti-ideal solutions. The utility degrees of the i^{th} alternative for the ideal and anti-ideal solutions are given by: $U_i^+ = \frac{\prod_{j=1}^{n} (\xi_{ij})^{v_{ij}}}{\sum_{j=1}^{n} v_j^+}$

$$U_i^- = -\frac{\sum_{j=1}^{n} v_j^-}{\prod_{j=1}^{n} \left(\xi_{ij}\right)^{v_{ij}}} + \max_{1 \le i \le m} \left(\frac{\sum_{j=1}^{n} v_j^-}{\prod_{j=1}^{n} \left(\xi_{ij}\right)^{v_{ij}}} \right) + \min_{1 \le i \le m} \left(\frac{\sum_{j=1}^{n} v_j^-}{\prod_{j=1}^{n} \left(\xi_{ij}\right)^{v_{ij}}} \right)$$

Where $v_j^+ = \max_{1 \le i \le m} \left(\xi_{ij} \cdot w_j\right)$ and $v_j^- = \min_{1 \le i \le m} \left(\xi_{ij} \cdot w_j\right)$ $\quad (i = 1, 2 \dots m; j = 1, 2 \dots n)$.

Step 11: Find out the utility function values based on the aggregated levels of utility by using Eq. (12).

$$\begin{aligned} f\left(U_i^+\right) &= \frac{U_i^+}{U_i^+ + U_i^-} \\ f\left(U_i^-\right) &= \frac{U_i^-}{U_i^+ + U_i^-} \end{aligned} \tag{12}$$

Step 12: The appraisal scores of the alternatives are calculated by using Eq. (13) with the parameter $\delta \in [0, 1]$.

$$AS_i = \left(U_i^+ + U_i^-\right) \frac{\left(1 + f\left(U_i^+\right)\right)^{\delta} \left(1 + f\left(U_i^-\right)\right)^{1-\delta} - \left(1 - f\left(U_i^+\right)\right)^{\delta} \left(1 - f\left(U_i^-\right)\right)^{1-\delta}}{\left(1 + f\left(U_i^+\right)\right)^{\delta} \left(1 + f\left(U_i^-\right)\right)^{1-\delta} + \left(1 - f\left(U_i^+\right)\right)^{\delta} \left(1 - f\left(U_i^-\right)\right)^{1-\delta}} \tag{13}$$

3.2. Pseudocode

Algorithm 1: Pseudocode for RFE and LOPCOW-ERUNS

Input: Enter the number of decision-makers, let's say d
Input: Enter the number of alternatives L and criterions cr
`// This will result in the following m matrices of order` $l \times cr$

$$\mathfrak{DM} = \begin{bmatrix} d\mathscr{A}_{11} & d\mathscr{A}_{12} & \cdots & d\mathscr{A}_{1k} \\ d\mathscr{A}_{21} & d\mathscr{A}_{22} & \cdots & d\mathscr{A}_{2k} \\ \cdots & \cdots & \cdots & \cdots \\ d\mathscr{A}_{m1} & d\mathscr{A}_{m2} & \cdots & d\mathscr{A}_{Lcr} \end{bmatrix}$$

$d\mathscr{A}_{ij} = (\langle \mathfrak{T}_{ij}, \mathfrak{F}_{ij} \rangle, \langle \alpha_{ij}, \beta_{ij} \rangle)$
`// Apply RFE Method`
Input: data, num_features_to_select
`// Find the score values`
while *length(selected_features) > num_features_to_select* **do**
  importance = mean(data(:, selected_features), 1)
  [~ least_important_feature] = min(importance)
  selected_features(least_important_feature) = [ ]
Output: selected_data
`// Apply LOPCOW Method`
`// First find the score values and` T_{ij} `matrices for each element`
for $i = 1$ **to** L **do**
  for $j = 1$ **to** cr **do**
    $Sc_{ij} = \frac{1}{2}\left[\frac{(\mathfrak{T}_{ij} - \mathfrak{F}_{ij} + 1)}{2} + \frac{(\alpha_{ij} - \beta_{ij} + 1)}{2}\right]$
for $i = 1$ **to** L **do**
  $prod_i$=1
  for $j = 1$ **to** cr **do**
    if $j == 1$ **then**
      $T_i(i, j) = 1$
    else
      $prod_i(i, j) = prod_i(i, j) * Sc_i(i, j)$
    $T_i(i, j) = prod_i(i, j)$
`// Find the softmax` Φ `for each element of decision makers matrics`
for $i = 1$ **to** L **do**
  $s_i = 0$
  for $j = 1$ **to** cr **do**
    $s_i = s_i + \exp(\frac{T_i(i,j)}{\sigma})$
  $sum\_phi_i = s_i$
for $i = 1$ **to** L **do**
  for $j = 1$ **to** cr **do**
    $\Phi_i(i, j) = \frac{\exp(\frac{T_i(i,j)}{\sigma})}{sum\_phi_i}$

3.3. Application

The global shift to RE is a critical response to climate change, environmental degradation, and the depletion of non-renewable resources. China, as the leading energy consumer and a significant producer of RE technologies, has achieved substantial advancements in transitioning to sustainable energy systems. Fig. 2 illustrates a horizontal bar chart that displays the installed RE capacity of the ten leading countries worldwide in 2023. China leads with 1,453 GW, followed by the U.S. at 388 GW, illustrating global leadership in sustainable energy development. Fig. 3 presents the geographical distribution and capacity of solar power facilities in China. The dots represent the locations, and the larger orange circles indicate higher capacities. This highlights the concentration of large solar installations in northern and eastern China, reflecting regions with abundant solar resources and developed infrastructure. This map demonstrates China's commitment to RE by emphasizing its substantial investment in solar power infrastructure. Fig. 4 illustrates the geographical distribution of wind power facilities across the country. The map employs purple dots to indicate the locations of these facilities, with the size and intensity of the dots reflecting the wind-generating capacity in megawatts (MW). The graphic shows that the northern and eastern regions primarily concentrate wind power. The western and southern regions exhibit sparse distributions. Shenzhen is a significant megacity located in southern China, serving as a crucial hub for innovation and technology. Shenzhen, home to over 20 million residents and a crucial hub in the Greater Bay Area, experiences significant energy demands, driven by rapid urbanization and industrial growth. The challenges, coupled with the city's commitment to China's carbon neutrality goal by 2060, underscore the imperative of transitioning to sustainable energy options. Shenzhen's abundant solar resources, proximity to the South China Sea for tidal and offshore wind energy, and advanced technological capabilities position it as a viable location for RE implementation. Fig. 5 illustrates the annual temperature variations in Shenzhen, emphasizing its subtropical climate, which features summer highs of 32 °C and winter lows around 12 °C, thus making it suitable for solar energy utilization. The city has demonstrated leadership in environmental initiatives, such as the electrification of its public transport fleet and the execution of smart grid projects, supported by robust municipal policies and financing. This research provides a systematic decision-making framework for Shenzhen and other cities to prioritize RE options based on various parameters. The assessment of each option will be conducted according to the fourteen criteria specified in Table 5 and the eight alternatives presented in Table 6 throughout the decision-making process. It identifies optimal solutions tailored to local conditions while minimizing

Algorithm 1: *Cont.*

// Apply the aggregation operator
for $i = 1$ **to** L **do**
  $prod_p = 1$ where p=1,2,3,4
  for $j = 1$ **to** cr **do**
    $prod_1 = prod_1 \times (1 - \mathfrak{T})^{\Phi_i(i,j)}$, $prod_2 = prod_2 \times (1 - \mathfrak{F})^{\Phi_i(i,j)}$
    $prod_3 = prod_3 \times (1 - \alpha)^{\Phi_i(i,j)}$, $prod_4 = prod_4 \times (1 - \beta)^{\Phi_i(i,j)}$
  $Agg_{ij} = \left(\langle 1 - prod_1, prod_2\rangle, \langle 1 - prod_3, prod_4\rangle\right)$
// Similarly, find the score value of aggregated decision matrix and normalise it
for $j = 1$ **to** cr **do**
  $s = 0$
  for $i = 1$ **to** L **do**
    $s = s + \widetilde{Sc}_{ij}^2$
  $P_j = |\ln \frac{\sqrt{\frac{s}{cr}}}{std(Sc_{ij})}| \times 100$
for $j = 1$ **to** cr **do**
  $w_j = \frac{P_j}{\sum P}$
// Apply ERUNS Method
Input: Enter the value of τ and λ
for $j = 1$ **to** cr **do**
  for $i = 1$ **to** L **do**
    $\phi_{ij} = (min(x(:,j))/x_{ij})^3 * \tau + (\lambda/min(x(:,j)))$
Input: Enter the value of k and δ
for $i = 1$ **to** L **do**
  for $j = 1$ **to** cr **do**
    if *j is benefit criteria* **then**
      $\xi_{ij} = -\phi_{ij} + \max(\phi(:,j)) + \min(\phi(:,j))$
    else if *j is cost criteria* **then**
      $\xi_{ij} = \xi_{ij}$
for $i = 1$ **to** L **do**
  for $j = 1$ **to** cr **do**
    $f_{ij} = \xi_{ij}/sum(\xi(i,:))$
for $i = 1$ **to** L **do**
  $s = 0$
  for $j = 1$ **to** cr **do**
    $s = s + (exp(f_{ij}/k) * w(j))$
  $sm(i) = s$
for $i = 1$ **to** L **do**
  for $j = 1$ **to** cr **do**
    $V_{ij} = (exp(f_{ij}/k) * w(j))/sm(i)$
    $V_+(j) = max(\xi(:,j) * w(j)), V_-(j) = min(\xi(:,j) * w(j))$
for $i = 1$ **to** L **do**
  $prod_1 = 1$
  for $j = 1$ **to** cr **do**
    $prod_1 = prod_1 * (\xi_{ij})^{V_{ij}}$
    $U_+(i) = prod_1/sum(V_+); prod_-(i) = prod1;$
    $\upsilon_2(i) = (sum(V_-)/prod_1);$
for $i = 1$ **to** L **do**
  $U_-(i) = -(sum(V_-)prod_-(i)) + max(\upsilon_2) + min(\upsilon_2)$
  for $i = 1$ **to** L **do**
    $fU_+(i) = U_+(i)/(U_+(i) + U_-(i))$,
    $fU_-(i) = U_-(i)/(U_+(i) + U_-(i))$
// Find the final appraisal scores
for $i = 1$ **to** L **do**
  $AS(i) = (U_+(i) + U_-(i)) * \frac{((1+fU_+(i))^{\delta})*((1+fU_-(i))^{1-\delta}) - ((1-fU_+(i))^{\delta})*((1-fU_-(i))^{1-\delta})}{((1+fU_+(i))^{\delta})*((1+fU_-(i))^{1-\delta}) + ((1-fU_+(i))^{\delta})*((1-fU_-(i))^{1-\delta})}$

environmental impacts, including pollution and land-use conflicts. The study highlights the importance of job development, public acceptance, and community engagement for effective implementation and sustained success. This study examines the unique challenges facing Shenzhen and leverages its advantages, supporting the city's goal of achieving carbon neutrality and offering a replicable framework for other rapidly urbanizing regions worldwide (see Table 4).

3.4. Decision-making process

Step 1.1: Start with all features mentioned in Table 5 and use the linguistic terms mentioned in Table 7 to input the LiDFNs corresponding to each alternative as shown in Table 8. The number of features to select is 5.

Step 1.2 and 1.3: Calculate the score values by using Eq. (2) as mentioned in Table 9 and importance of each feature by using Eq. (3). The selected features are $Cr_2, Cr_3, Cr_{10}, Cr_{12}, Cr_{13}$.

Step 2: Decision makers provide their expert value through LiDFNs for each alternative under the selected features, as shown in Table 10.

Step 3: The aggregated values obtained by applying the LiDFSMA operator is shown in Table 11.

Step 4: The score matrix Sc_{ij} of the aggregated decision matrix by applying Equation (2) and the normalize of this matrix using (6) is shown below.

$$Sc_{ij} = \begin{bmatrix} 0.6275 & 0.6850 & 0.7475 & 0.5875 & 0.8050 \\ 0.4525 & 0.6225 & 0.6825 & 0.6700 & 0.5925 \\ 0.4975 & 0.5825 & 0.6050 & 0.6575 & 0.4975 \\ 0.4650 & 0.5200 & 0.6325 & 0.6700 & 0.4675 \\ 0.4225 & 0.5625 & 0.5725 & 0.5775 & 0.4625 \\ 0.5200 & 0.5950 & 0.5775 & 0.5325 & 0.4700 \\ 0.3775 & 0.5525 & 0.5350 & 0.5800 & 0.4825 \\ 0.3900 & 0.5600 & 0.5500 & 0.5575 & 0.5075 \end{bmatrix}$$

$$\widetilde{Sc}_{ij} = \begin{bmatrix} 0.0 & 1.0 & 1.0 & 0.6000 & 1.0 \\ 0.7000 & 0.6212 & 0.6941 & 0.0 & 0.3796 \\ 0.5200 & 0.3788 & 0.3294 & 0.0909 & 0.1022 \\ 0.6500 & 0.0 & 0.4588 & 0.0 & 0.0146 \\ 0.8200 & 0.2576 & 0.1765 & 0.6727 & 0.0 \\ 0.4300 & 0.4545 & 0.2000 & 1.0 & 0.0219 \\ 1.0 & 0.1970 & 0.0 & 0.6545 & 0.0584 \\ 0.9500 & 0.2424 & 0.0706 & 0.8182 & 0.1314 \end{bmatrix}$$

Step 5 and 6: The percentage value for the criteria by using Eq. (7) and the weight of each criterion calculated using Eq. (8) is shown in Table 12.

Step 7 and 8: The standardization of the elements of the matrix Sc to the interval $[0,1]$ is carried out by using Eq. (9) and the criterion is of the max type, the values of $\mathfrak{X}^N = \left[\mathfrak{T}_{ij}\right]_{m\times n}$ are modified by applying Eq. (10) and represented in the matrix below is represented in the below matrix.

$$\mathfrak{T}_{ij} = \begin{bmatrix} 0.2177 & 0.4375 & 0.3666 & 0.7446 & 0.1896 \\ 0.5806 & 0.5829 & 0.4817 & 0.5020 & 0.4756 \\ 0.4369 & 0.7114 & 0.6915 & 0.5312 & 0.8034 \\ 0.5350 & 1.0000 & 0.6052 & 0.5020 & 0.9683 \\ 0.7133 & 0.7900 & 0.8161 & 0.7840 & 1.0000 \\ 0.3826 & 0.6675 & 0.7951 & 1.0000 & 0.9529 \\ 1.0000 & 0.8337 & 1.0000 & 0.7739 & 0.8807 \\ 0.9069 & 0.8007 & 0.9204 & 0.8714 & 0.7569 \end{bmatrix}$$

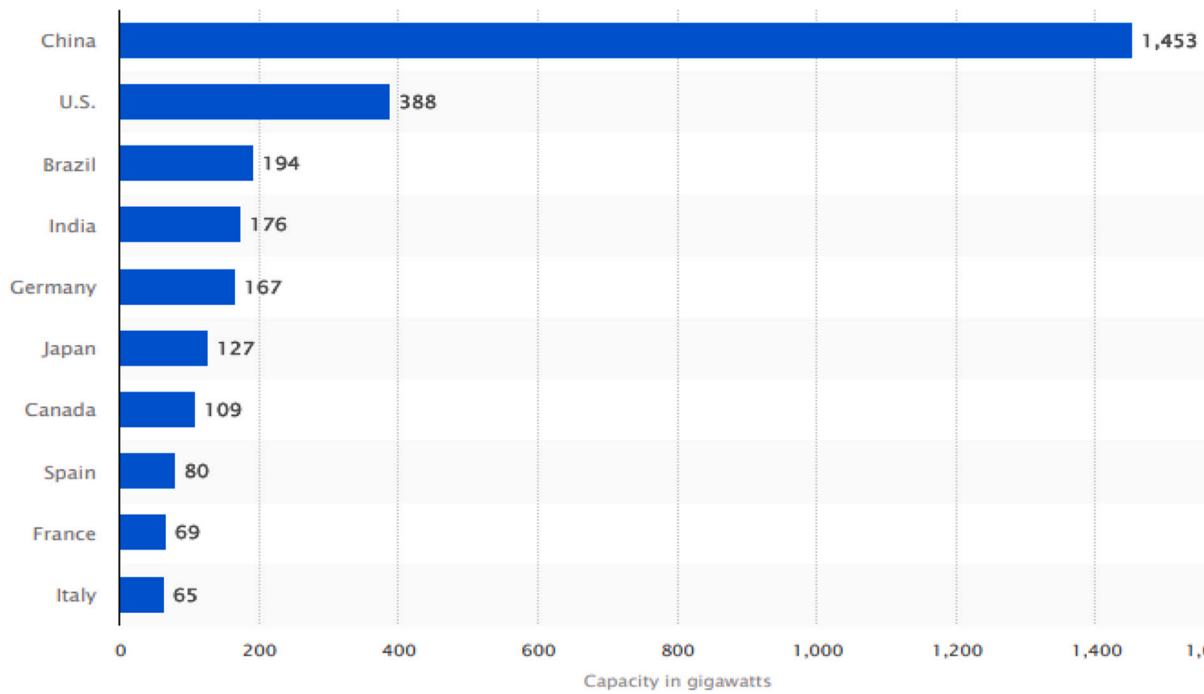

Fig. 2. RE capacity (GW) of the top 10 countries worldwide.

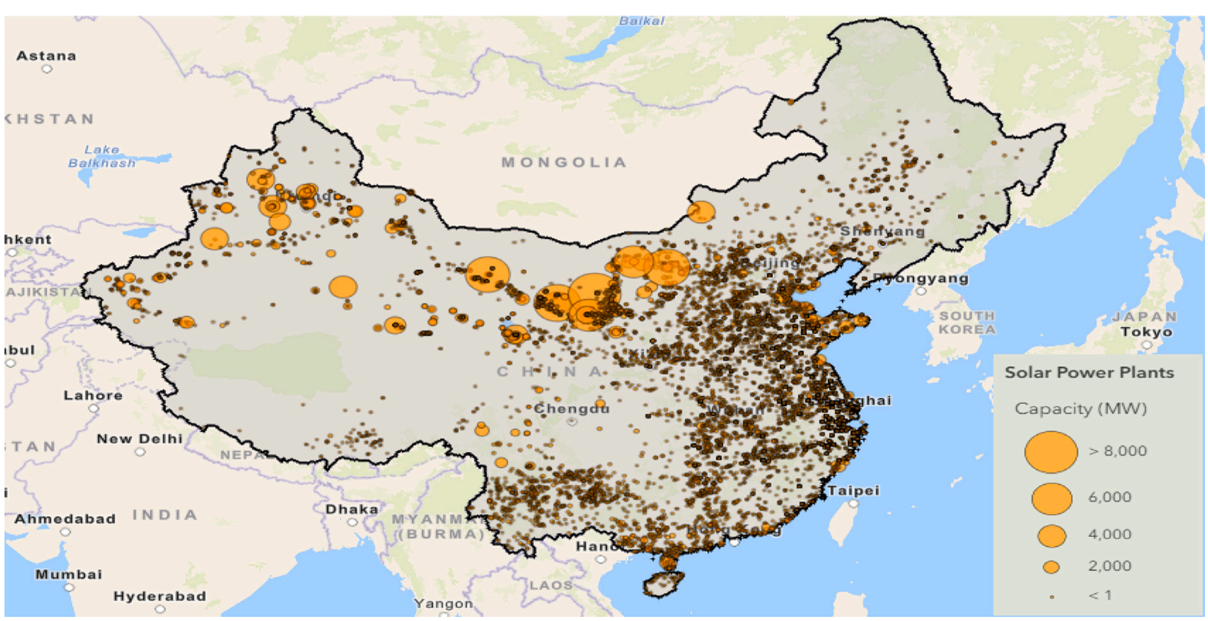

Fig. 3. Geographical distribution and capacity of solar power plants in China.

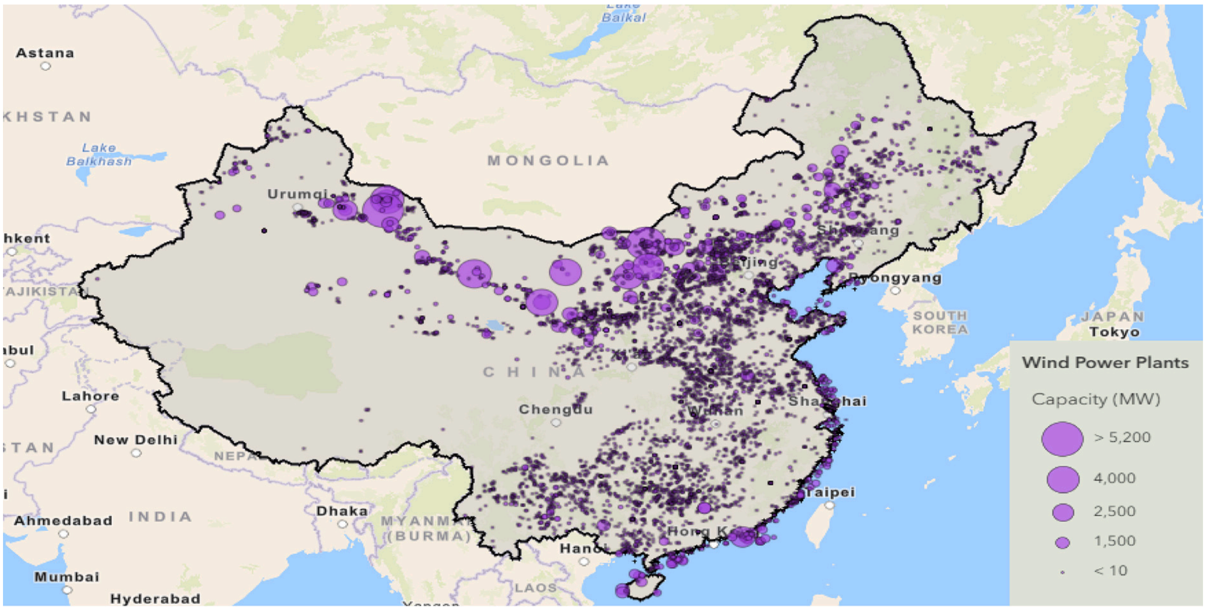

Fig. 4. Geographical distribution and capacity of wind power plants in China.

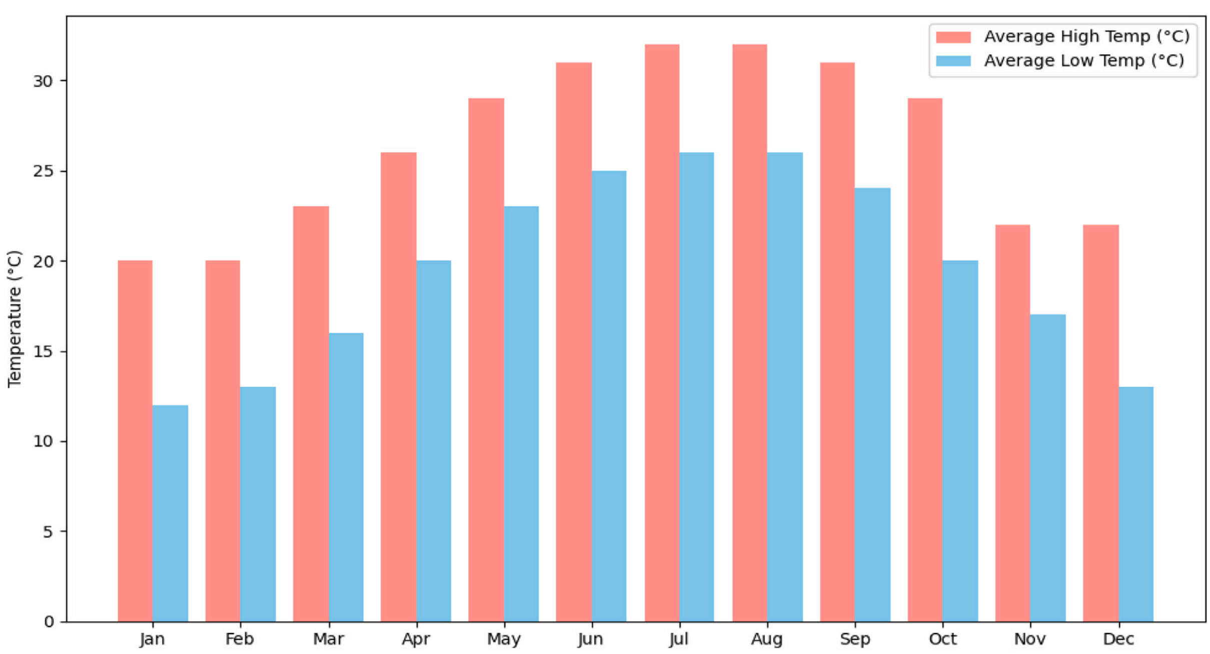

Fig. 5. Annual temperature variation in Shenzhen.

Table 4
RE alternatives in Shenzhen with importance levels.

Alternative	Energy output (%)	Initial investment ($/kW)	Suitability for Shenzhen	Environmental impact
Wind Power (Offshore)	30–45	1200–1700	High (Coastal wind resources) $I.L_1$	Low (No emissions; some impact on marine ecosystems) $I.L_2$
Hydropower	50–90	1500–2000	Limited (Urban constraints limit feasibility of large dams) $I.L_5$	High (Significant impact on aquatic ecosystems and biodiversity) $I.L_5$
Biomass Energy	50–80	2000–3000	Moderate (Urban waste-to-energy potential) $I.L_5$	Moderate (Emissions from combustion; potential reduction in landfill waste) $I.L_7$
Geothermal Energy	70–90	2500–5000	Limited (Lack of geothermal activity in Shenzhen) $I.L_6$	Low (Minimal emissions, but localized land subsidence risks) $I.L_2$
Tidal Energy	35–60	3000–5000	High (Coastal infrastructure supports feasibility) $I.L_3$	Low (Potential impact on tidal flows and marine life) $I.L_2$
Wave Energy	20–30	3500–6000	Moderate (Technological development needed for large-scale application) $I.L_4$	Low (No emissions; potential impact on marine ecosystems) $I.L_3$
Solar Power (Photovoltaic)	15–25	800–1200	High (Urban rooftop installations and abundant sunlight) $I.L_1$	Low (Minimal emissions during operation; potential land use issues) $I.L_1$
Solar Thermal Power	20–40	4000–7000	High (Requires large-scale installation space) $I.L_2$	Low (Minimal emissions; larger installations could disrupt land use) $I.L_1$

Table 5
Definitions of each criterion.

Criteria	Definitions
Sustainability $\mathtt{Cr}_1$	The measure of the capacity of energy sources to continuously supply end consumers with energy is sustainability. Selling the energy product depends on consumer satisfaction, which this criteria establishes.
Impact on the environment $\mathtt{Cr}_2$	Decreased emissions and impact on the environment. Effects on local ecosystems and species richness. Using resources and creating trash.
Energy output $\mathtt{Cr}_3$	Capacity factor, and total energy produced. Future scalability and integration with the current grid.
Affordability $\mathtt{Cr}_4$	It is determined by calculating the average price and subsequently monitoring the extent to which the energy price fluctuates about that average.
Technical expertise $\mathtt{Cr}_5$	It assesses the proficiency of local employees in managing the utilized technology. Given that RE plants are predominantly situated in distant regions, it is crucial to take into account the accessibility of local labour for carrying out maintenance tasks.
Labour impact $\mathtt{Cr}_6$	An effective method of assessing RE is by examining its impact on employment, both in terms of direct and indirect effects.
Economic value $\mathtt{Cr}_7$	This criterion is utilized to ascertain the capital's rate of return for RE installations.
Performance consistency and predictability $\mathtt{Cr}_8$	Through the application of this criterion, the performance of the technology that is utilized for the production of RE is evaluated.
Risk $\mathtt{Cr}_9$	By employing this criterion, the potential for the energy strategy and technology that is now being utilized to fail is evaluated and evaluated accurately.
Public Acceptance $\mathtt{Cr}_{10}$	Visual impact and its integration into the local environment. Other annoyances and noise pollution. Participation in decision-making processes and community support.
Pollutant $\mathtt{Cr}_{11}$	The criterion is employed to evaluate the quantity of any pollutant discharged from the RE generation system, encompassing all forms of detrimental substances released into the environment, including CO2, liquid waste, and solid waste.
Land and space requirements $\mathtt{Cr}_{12}$	The area of land needed to install something. suitability of the climate and geography of the area. consequences for land use and possible disputes with other land uses.
Cost efficiency $\mathtt{Cr}_{13}$	The initial investment is for installation and continuous maintenance expenditures, including any prospective rewards or subsidies from the government. Evaluation of the long-term financial benefits of non-renewable resources.
Distance to user $\mathtt{Cr}_{14}$	This criterion is crucial for considering electricity transmission losses and construction costs.

Table 6
Definitions of each alternative.

Alternative	Definitions
Solar power (Photovoltaic) $\mathfrak{Al}_1$	It produces power from sunlight by employing photovoltaic cells. mounted in locations with strong solar radiation, such as solar farms or rooftops. renowned for producing power without emitting greenhouse gases and having a negligible operational impact on the environment.
Wave energy $\mathfrak{Al}_2$	Generates electricity from the kinetic energy of ocean waves by employing attenuators, oscillating water columns, and point absorbing. Possessing significant power potential in coastal areas, while it is still in its infancy and confronts environmental and technological obstacles.
Hydropower $\mathfrak{Al}_3$	Dams or run-of-the-river systems generate energy from flowing or falling water. Consistent energy output requires specific geographic circumstances and may have severe ecological and socioeconomic consequences.
Biomass energy $\mathfrak{Al}_4$	Produces energy using organic materials such as agricultural wastes, wood pellets, and waste goods. Biomass is burned or processed into biofuels. Can decrease waste and is considered carbon-neutral, however, sustainability is determined by source and land use practices.
Geothermal energy $\mathfrak{Al}_5$	Utilizes heat from beneath the Earth's surface to produce electricity. Reservoirs of hot water or steam are located underneath power turbines. Provides consistent power with a low environmental impact but is location-specific.
Tidal energy $\mathfrak{Al}_6$	Tidal stream generators or tidal barrages use the rising and falling of sea levels (tides) to create electricity. Highly predictable and capable of producing large power, but only in places with strong tidal movements and the potential to harm marine environments.
Wind power $\mathfrak{Al}_7$	It utilizes turbines to produce power from wind. installed offshore or on land (onshore). transforms wind energy from kinetic to mechanical and finally electrical power. Low operating emissions and high energy output, however, have an impact on noise and sight and require constant wind speeds.
Solar thermal power $\mathfrak{Al}_8$	Concentrates sunlight by the use of mirrors or lenses to create heat and steam, which powers turbines to produce energy. Ideal for regions with lots of direct sunshine, it can produce consistent power with thermal storage but comes with a hefty initial cost and demands a large amount of land.

Table 7
Generalized linguistic terms and their corresponding LiDFNs.

Linguistic term	Abbreviation	LiDFNs
Importance level$_1$	$I.L_1$	$(\langle 1-0.05(0), 0+0.05(0)\rangle, \langle 0.8-\frac{0.05(0)}{2}, 0.2+\frac{0.05(0)}{2}\rangle)$
Importance level$_2$	$I.L_2$	$(\langle 1-0.05(1), 0+0.05(1)\rangle, \langle 0.8-\frac{0.05(1)}{2}, 0.2+\frac{0.05(1)}{2}\rangle)$
$\vdots$	$\vdots$	$\vdots$
Importance level$_h$	$I.L_h$	$(\langle 1-0.05(h-1), 0+0.05(h-1)\rangle, \langle 0.8-\frac{0.05(h)}{2}, 0.2+\frac{0.05(h)}{2}\rangle)$
$\vdots$	$\vdots$	$\vdots$
Importance level$_n$	$I.L_n$	$(\langle 1-0.05(n-1), 0+0.05(n-1)\rangle, \langle 0.8-\frac{0.05(n)}{2}, 0.2+\frac{0.05(n)}{2}\rangle)$

Table 8
Alternatives and criteria evaluations with linguistic terms.

Alternatives	$\mathtt{Cr}_1$	$\mathtt{Cr}_2$	$\mathtt{Cr}_3$	$\mathtt{Cr}_4$	$\mathtt{Cr}_5$	$\mathtt{Cr}_6$	$\mathtt{Cr}_7$	$\mathtt{Cr}_8$	$\mathtt{Cr}_9$	$\mathtt{Cr}_{10}$	$\mathtt{Cr}_{11}$	$\mathtt{Cr}_{12}$	$\mathtt{Cr}_{13}$	$\mathtt{Cr}_{14}$
$\mathfrak{Al}_1$	$I.L_3$	$I.L_5$	$I.L_7$	$I.L_{12}$	$I.L_9$	$I.L_{14}$	$I.L_6$	$I.L_{10}$	$I.L_{13}$	$I.L_8$	$I.L_{11}$	$I.L_2$	$I.L_4$	$I.L_1$
$\mathfrak{Al}_2$	$I.L_{11}$	$I.L_{14}$	$I.L_2$	$I.L_5$	$I.L_8$	$I.L_7$	$I.L_3$	$I.L_6$	$I.L_{10}$	$I.L_4$	$I.L_9$	$I.L_{12}$	$I.L_1$	$I.L_{13}$
$\mathfrak{Al}_3$	$I.L_9$	$I.L_6$	$I.L_{14}$	$I.L_3$	$I.L_{12}$	$I.L_8$	$I.L_{10}$	$I.L_1$	$I.L_5$	$I.L_{13}$	$I.L_2$	$I.L_4$	$I.L_7$	$I.L_{11}$
$\mathfrak{Al}_4$	$I.L_{10}$	$I.L_1$	$I.L_3$	$I.L_{13}$	$I.L_7$	$I.L_{11}$	$I.L_{12}$	$I.L_9$	$I.L_8$	$I.L_5$	$I.L_4$	$I.L_6$	$I.L_2$	$I.L_{14}$
$\mathfrak{Al}_5$	$I.L_7$	$I.L_8$	$I.L_4$	$I.L_6$	$I.L_{11}$	$I.L_3$	$I.L_9$	$I.L_2$	$I.L_{12}$	$I.L_1$	$I.L_{13}$	$I.L_{10}$	$I.L_5$	$I.L_{14}$
$\mathfrak{Al}_6$	$I.L_6$	$I.L_{13}$	$I.L_5$	$I.L_{10}$	$I.L_1$	$I.L_{12}$	$I.L_{11}$	$I.L_8$	$I.L_2$	$I.L_{14}$	$I.L_9$	$I.L_4$	$I.L_3$	$I.L_7$
$\mathfrak{Al}_7$	$I.L_{12}$	$I.L_2$	$I.L_1$	$I.L_7$	$I.L_9$	$I.L_{10}$	$I.L_4$	$I.L_{14}$	$I.L_3$	$I.L_6$	$I.L_{13}$	$I.L_5$	$I.L_{11}$	$I.L_8$
$\mathfrak{Al}_8$	$I.L_{13}$	$I.L_9$	$I.L_6$	$I.L_4$	$I.L_{10}$	$I.L_2$	$I.L_5$	$I.L_{11}$	$I.L_7$	$I.L_1$	$I.L_{12}$	$I.L_3$	$I.L_{14}$	$I.L_8$

Table 9
Alternatives and criteria evaluations with score values.

Alternatives	$\mathtt{Cr}_1$	$\mathtt{Cr}_2$	$\mathtt{Cr}_3$	$\mathtt{Cr}_4$	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10	Cr11	Cr12	Cr13	Cr14
$\mathfrak{Al}_1$	0.8250	0.7500	0.6750	0.4875	0.6000	0.4125	0.7125	0.5625	0.4500	0.6375	0.5250	0.8625	0.7875	0.9000
$\mathfrak{Al}_2$	0.5250	0.4125	0.8625	0.7500	0.6375	0.6750	0.8250	0.7125	0.5625	0.7875	0.6000	0.4875	0.9000	0.4500
$\mathfrak{Al}_3$	0.6000	0.7125	0.4125	0.8250	0.4875	0.6375	0.5625	0.9000	0.7500	0.4500	0.8625	0.7875	0.6750	0.5250
$\mathfrak{Al}_4$	0.5625	0.9000	0.8250	0.4500	0.6750	0.5250	0.4875	0.6000	0.6375	0.7500	0.7875	0.7125	0.8625	0.4125
$\mathfrak{Al}_5$	0.6750	0.6375	0.7875	0.7125	0.5250	0.8250	0.6000	0.8625	0.4875	0.9000	0.4500	0.5625	0.7500	0.4125
$\mathfrak{Al}_6$	0.7125	0.4500	0.7500	0.5625	0.9000	0.4875	0.5250	0.6375	0.8625	0.4125	0.6000	0.7875	0.8250	0.6750
$\mathfrak{Al}_7$	0.4875	0.8625	0.9000	0.6750	0.6000	0.5625	0.7875	0.4125	0.8250	0.7125	0.4500	0.7500	0.5250	0.6375
$\mathfrak{Al}_8$	0.4500	0.6000	0.7125	0.7875	0.5625	0.8625	0.7500	0.5250	0.6750	0.9000	0.4875	0.8250	0.4125	0.6375

Table 10
Decision maker utilizes LiDFS for input.

DMs	Alternatives	Cr_2	Cr_3	Cr_{10}	Cr_{12}	Cr_{13}
$\mathfrak{DM}_1$	$\mathfrak{Al}_1$	$(\langle 0.34, 0.89\rangle, \langle 0.29, 0.75\rangle)$	$(\langle 0.97, 0.63\rangle, \langle 0.58, 0.24\rangle)$	$(\langle 0.79, 0.18\rangle, \langle 0.59, 0.14\rangle)$	$(\langle 0.56, 0.31\rangle, \langle 0.67, 0.15\rangle)$	$(\langle 0.92, 0.29\rangle, \langle 0.85, 0.14\rangle)$
	$\mathfrak{Al}_2$	$(\langle 0.19, 0.53\rangle, \langle 0.33, 0.44\rangle)$	$(\langle 0.71, 0.53\rangle, \langle 0.71, 0.24\rangle)$	$(\langle 0.74, 0.23\rangle, \langle 0.39, 0.39\rangle)$	$(\langle 0.67, 0.42\rangle, \langle 0.51, 0.42\rangle)$	$(\langle 0.72, 0.15\rangle, \langle 0.24, 0.35\rangle)$
	$\mathfrak{Al}_3$	$(\langle 0.31, 0.73\rangle, \langle 0.45, 0.23\rangle)$	$(\langle 0.49, 0.55\rangle, \langle 0.39, 0.48\rangle)$	$(\langle 0.61, 0.27\rangle, \langle 0.54, 0.51\rangle)$	$(\langle 0.73, 0.51\rangle, \langle 0.33, 0.33\rangle)$	$(\langle 0.47, 0.69\rangle, \langle 0.39, 0.37\rangle)$
	$\mathfrak{Al}_4$	$(\langle 0.36, 0.58\rangle, \langle 0.25, 0.63\rangle)$	$(\langle 0.68, 0.62\rangle, \langle 0.21, 0.23\rangle)$	$(\langle 0.71, 0.45\rangle, \langle 0.31, 0.34\rangle)$	$(\langle 0.89, 0.23\rangle, \langle 0.49, 0.47\rangle)$	$(\langle 0.89, 0.99\rangle, \langle 0.15, 0.36\rangle)$
	$\mathfrak{Al}_5$	$(\langle 0.42, 0.81\rangle, \langle 0.29, 0.62\rangle)$	$(\langle 0.62, 0.69\rangle, \langle 0.43, 0.27\rangle)$	$(\langle 0.52, 0.34\rangle, \langle 0.49, 0.46\rangle)$	$(\langle 0.71, 0.53\rangle, \langle 0.31, 0.27\rangle)$	$(\langle 0.63, 0.55\rangle, \langle 0.49, 0.23\rangle)$
	$\mathfrak{Al}_6$	$(\langle 0.34, 0.72\rangle, \langle 0.41, 0.27\rangle)$	$(\langle 0.63, 0.49\rangle, \langle 0.53, 0.38\rangle)$	$(\langle 0.42, 0.34\rangle, \langle 0.54, 0.51\rangle)$	$(\langle 0.75, 0.64\rangle, \langle 0.32, 0.32\rangle)$	$(\langle 0.52, 0.67\rangle, \langle 0.54, 0.36\rangle)$
	$\mathfrak{Al}_7$	$(\langle 0.27, 0.69\rangle, \langle 0.21, 0.69\rangle)$	$(\langle 0.56, 0.58\rangle, \langle 0.41, 0.21\rangle)$	$(\langle 0.49, 0.31\rangle, \langle 0.41, 0.41\rangle)$	$(\langle 0.71, 0.47\rangle, \langle 0.31, 0.28\rangle)$	$(\langle 0.37, 0.49\rangle, \langle 0.51, 0.32\rangle)$
	$\mathfrak{Al}_8$	$(\langle 0.29, 0.71\rangle, \langle 0.21, 0.69\rangle)$	$(\langle 0.71, 0.68\rangle, \langle 0.41, 0.21\rangle)$	$(\langle 0.51, 0.29\rangle, \langle 0.41, 0.37\rangle)$	$(\langle 0.77, 0.61\rangle, \langle 0.32, 0.32\rangle)$	$(\langle 0.41, 0.47\rangle, \langle 0.52, 0.28\rangle)$
$\mathfrak{DM}_2$	$\mathfrak{Al}_1$	$(\langle 0.87, 0.48\rangle, \langle 0.45, 0.32\rangle)$	$(\langle 0.81, 0.45\rangle, \langle 0.28, 0.45\rangle)$	$(\langle 0.95, 0.82\rangle, \langle 0.39, 0.61\rangle)$	$(\langle 0.47, 0.28\rangle, \langle 0.76, 0.63\rangle)$	$(\langle 0.45, 0.22\rangle, \langle 0.45, 0.23\rangle)$
	$\mathfrak{Al}_2$	$(\langle 0.65, 0.33\rangle, \langle 0.28, 0.43\rangle)$	$(\langle 0.63, 0.53\rangle, \langle 0.38, 0.25\rangle)$	$(\langle 0.42, 0.33\rangle, \langle 0.34, 0.55\rangle)$	$(\langle 0.62, 0.35\rangle, \langle 0.28, 0.32\rangle)$	$(\langle 0.48, 0.64\rangle, \langle 0.33, 0.19\rangle)$
	$\mathfrak{Al}_3$	$(\langle 0.27, 0.49\rangle, \langle 0.34, 0.28\rangle)$	$(\langle 0.48, 0.92\rangle, \langle 0.28, 0.44\rangle)$	$(\langle 0.67, 0.25\rangle, \langle 0.39, 0.23\rangle)$	$(\langle 0.44, 0.45\rangle, \langle 0.47, 0.25\rangle)$	$(\langle 0.57, 0.35\rangle, \langle 0.68, 0.18\rangle)$
	$\mathfrak{Al}_4$	$(\langle 0.83, 0.61\rangle, \langle 0.24, 0.42\rangle)$	$(\langle 0.65, 0.37\rangle, \langle 0.32, 0.64\rangle)$	$(\langle 0.34, 0.64\rangle, \langle 0.49, 0.42\rangle)$	$(\langle 0.35, 0.81\rangle, \langle 0.32, 0.42\rangle)$	$(\langle 0.32, 0.36\rangle, \langle 0.24, 0.44\rangle)$
	$\mathfrak{Al}_5$	$(\langle 0.55, 0.31\rangle, \langle 0.41, 0.21\rangle)$	$(\langle 0.65, 0.42\rangle, \langle 0.36, 0.15\rangle)$	$(\langle 0.76, 0.55\rangle, \langle 0.22, 0.18\rangle)$	$(\langle 0.82, 0.67\rangle, \langle 0.38, 0.22\rangle)$	$(\langle 0.41, 0.36\rangle, \langle 0.51, 0.23\rangle)$
	$\mathfrak{Al}_6$	$(\langle 0.34, 0.54\rangle, \langle 0.29, 0.34\rangle)$	$(\langle 0.49, 0.67\rangle, \langle 0.39, 0.41\rangle)$	$(\langle 0.57, 0.75\rangle, \langle 0.44, 0.53\rangle)$	$(\langle 0.69, 0.87\rangle, \langle 0.57, 0.64\rangle)$	$(\langle 0.73, 0.91\rangle, \langle 0.65, 0.72\rangle)$
	$\mathfrak{Al}_7$	$(\langle 0.36, 0.61\rangle, \langle 0.25, 0.36\rangle)$	$(\langle 0.45, 0.65\rangle, \langle 0.41, 0.39\rangle)$	$(\langle 0.56, 0.74\rangle, \langle 0.43, 0.54\rangle)$	$(\langle 0.67, 0.84\rangle, \langle 0.54, 0.63\rangle)$	$(\langle 0.75, 0.95\rangle, \langle 0.67, 0.71\rangle)$
	$\mathfrak{Al}_8$	$(\langle 0.33, 0.66\rangle, \langle 0.21, 0.31\rangle)$	$(\langle 0.47, 0.73\rangle, \langle 0.37, 0.42\rangle)$	$(\langle 0.55, 0.81\rangle, \langle 0.42, 0.57\rangle)$	$(\langle 0.65, 0.93\rangle, \langle 0.51, 0.61\rangle)$	$(\langle 0.72, 0.65\rangle, \langle 0.46, 0.49\rangle)$
$\mathfrak{DM}_3$	$\mathfrak{Al}_1$	$(\langle 0.49, 0.38\rangle, \langle 0.48, 0.34\rangle)$	$(\langle 0.64, 0.28\rangle, \langle 0.62, 0.23\rangle)$	$(\langle 0.68, 0.24\rangle, \langle 0.39, 0.19\rangle)$	$(\langle 0.89, 0.18\rangle, \langle 0.33, 0.34\rangle)$	$(\langle 0.69, 0.18\rangle, \langle 0.38, 0.29\rangle)$
	$\mathfrak{Al}_2$	$(\langle 0.28, 0.48\rangle, \langle 0.33, 0.33\rangle)$	$(\langle 0.47, 0.28\rangle, \langle 0.22, 0.39\rangle)$	$(\langle 0.39, 0.19\rangle, \langle 0.62, 0.23\rangle)$	$(\langle 0.28, 0.62\rangle, \langle 0.42, 0.41\rangle)$	$(\langle 0.62, 0.49\rangle, \langle 0.23, 0.33\rangle)$
	$\mathfrak{Al}_3$	$(\langle 0.82, 0.63\rangle, \langle 0.23, 0.48\rangle)$	$(\langle 0.64, 0.83\rangle, \langle 0.61, 0.34\rangle)$	$(\langle 0.28, 0.63\rangle, \langle 0.33, 0.43\rangle)$	$(\langle 0.39, 0.88\rangle, \langle 0.28, 0.12\rangle)$	$(\langle 0.63, 0.83\rangle, \langle 0.48, 0.48\rangle)$
	$\mathfrak{Al}_4$	$(\langle 0.39, 0.68\rangle, \langle 0.18, 0.39\rangle)$	$(\langle 0.48, 0.43\rangle, \langle 0.28, 0.48\rangle)$	$(\langle 0.19, 0.48\rangle, \langle 0.34, 0.32\rangle)$	$(\langle 0.42, 0.61\rangle, \langle 0.23, 0.62\rangle)$	$(\langle 0.43, 0.38\rangle, \langle 0.62, 0.23\rangle)$
	$\mathfrak{Al}_5$	$(\langle 0.48, 0.67\rangle, \langle 0.28, 0.38\rangle)$	$(\langle 0.57, 0.78\rangle, \langle 0.38, 0.48\rangle)$	$(\langle 0.67, 0.82\rangle, \langle 0.47, 0.58\rangle)$	$(\langle 0.77, 0.92\rangle, \langle 0.58, 0.67\rangle)$	$(\langle 0.82, 0.58\rangle, \langle 0.38, 0.47\rangle)$
	$\mathfrak{Al}_6$	$(\langle 0.48, 0.58\rangle, \langle 0.39, 0.48\rangle)$	$(\langle 0.58, 0.68\rangle, \langle 0.48, 0.58\rangle)$	$(\langle 0.68, 0.78\rangle, \langle 0.58, 0.68\rangle)$	$(\langle 0.78, 0.88\rangle, \langle 0.68, 0.78\rangle)$	$(\langle 0.88, 0.98\rangle, \langle 0.78, 0.88\rangle)$
	$\mathfrak{Al}_7$	$(\langle 0.39, 0.69\rangle, \langle 0.28, 0.39\rangle)$	$(\langle 0.48, 0.79\rangle, \langle 0.38, 0.48\rangle)$	$(\langle 0.59, 0.88\rangle, \langle 0.49, 0.58\rangle)$	$(\langle 0.69, 0.98\rangle, \langle 0.59, 0.69\rangle)$	$(\langle 0.79, 0.69\rangle, \langle 0.49, 0.59\rangle)$
	$\mathfrak{Al}_8$	$(\langle 0.34, 0.54\rangle, \langle 0.26, 0.34\rangle)$	$(\langle 0.44, 0.66\rangle, \langle 0.36, 0.44\rangle)$	$(\langle 0.54, 0.76\rangle, \langle 0.46, 0.54\rangle)$	$(\langle 0.64, 0.86\rangle, \langle 0.56, 0.64\rangle)$	$(\langle 0.74, 0.56\rangle, \langle 0.34, 0.46\rangle)$

Table 11
Aggregated decision matrix.

Alternatives	Cr_2	Cr_3	Cr_{10}	Cr_{12}	Cr_{13}
$\mathfrak{Al}_1$	$(\langle 0.61, 0.34\rangle, \langle 0.45, 0.21\rangle)$	$(\langle 0.84, 0.29\rangle, \langle 0.72, 0.53\rangle)$	$(\langle 0.76, 0.19\rangle, \langle 0.67, 0.25\rangle)$	$(\langle 0.52, 0.61\rangle, \langle 0.78, 0.34\rangle)$	$(\langle 0.98, 0.42\rangle, \langle 0.91, 0.25\rangle)$
$\mathfrak{Al}_2$	$(\langle 0.28, 0.49\rangle, \langle 0.41, 0.39\rangle)$	$(\langle 0.62, 0.47\rangle, \langle 0.63, 0.29\rangle)$	$(\langle 0.83, 0.24\rangle, \langle 0.55, 0.41\rangle)$	$(\langle 0.79, 0.36\rangle, \langle 0.74, 0.49\rangle)$	$(\langle 0.81, 0.15\rangle, \langle 0.33, 0.62\rangle)$
$\mathfrak{Al}_3$	$(\langle 0.53, 0.67\rangle, \langle 0.36, 0.23\rangle)$	$(\langle 0.67, 0.53\rangle, \langle 0.48, 0.29\rangle)$	$(\langle 0.72, 0.38\rangle, \langle 0.59, 0.51\rangle)$	$(\langle 0.84, 0.49\rangle, \langle 0.61, 0.33\rangle)$	$(\langle 0.59, 0.71\rangle, \langle 0.48, 0.37\rangle)$
$\mathfrak{Al}_4$	$(\langle 0.47, 0.61\rangle, \langle 0.39, 0.52\rangle)$	$(\langle 0.79, 0.56\rangle, \langle 0.34, 0.29\rangle)$	$(\langle 0.83, 0.41\rangle, \langle 0.47, 0.36\rangle)$	$(\langle 0.94, 0.32\rangle, \langle 0.67, 0.61\rangle)$	$(\langle 0.96, 0.88\rangle, \langle 0.21, 0.42\rangle)$
$\mathfrak{Al}_5$	$(\langle 0.67, 0.78\rangle, \langle 0.41, 0.61\rangle)$	$(\langle 0.74, 0.71\rangle, \langle 0.54, 0.32\rangle)$	$(\langle 0.61, 0.47\rangle, \langle 0.67, 0.52\rangle)$	$(\langle 0.79, 0.69\rangle, \langle 0.53, 0.32\rangle)$	$(\langle 0.72, 0.63\rangle, \langle 0.67, 0.49\rangle)$
$\mathfrak{Al}_6$	$(\langle 0.59, 0.67\rangle, \langle 0.48, 0.32\rangle)$	$(\langle 0.71, 0.54\rangle, \langle 0.62, 0.41\rangle)$	$(\langle 0.58, 0.39\rangle, \langle 0.63, 0.51\rangle)$	$(\langle 0.83, 0.72\rangle, \langle 0.45, 0.43\rangle)$	$(\langle 0.61, 0.73\rangle, \langle 0.63, 0.38\rangle)$
$\mathfrak{Al}_7$	$(\langle 0.46, 0.67\rangle, \langle 0.39, 0.67\rangle)$	$(\langle 0.63, 0.62\rangle, \langle 0.52, 0.32\rangle)$	$(\langle 0.57, 0.43\rangle, \langle 0.52, 0.52\rangle)$	$(\langle 0.79, 0.56\rangle, \langle 0.48, 0.39\rangle)$	$(\langle 0.52, 0.59\rangle, \langle 0.68, 0.43\rangle)$
$\mathfrak{Al}_8$	$(\langle 0.39, 0.58\rangle, \langle 0.41, 0.66\rangle)$	$(\langle 0.78, 0.67\rangle, \langle 0.52, 0.39\rangle)$	$(\langle 0.62, 0.47\rangle, \langle 0.52, 0.47\rangle)$	$(\langle 0.84, 0.63\rangle, \langle 0.45, 0.43\rangle)$	$(\langle 0.56, 0.53\rangle, \langle 0.69, 0.38\rangle)$

Table 12
Standard deviation, percentage value and criterion weights.

Description	Cr_2	Cr_3	Cr_{10}	Cr_{12}	Cr_{13}
Standard deviation	0.3228	0.3067	0.3390	0.3926	0.3404
Percentage value	77.6805	46.3107	35.6968	43.0798	11.8858
Weight	0.3619	0.2157	0.1663	0.2007	0.0554

$$\xi_{ij} = \begin{bmatrix} 0.2177 & 1.0000 & 1.0000 & 0.7446 & 1.0000 \\ 0.5806 & 0.8546 & 0.8850 & 0.5020 & 0.7140 \\ 0.4369 & 0.7260 & 0.6751 & 0.5312 & 0.3862 \\ 0.5350 & 0.4375 & 0.7615 & 0.5020 & 0.2214 \\ 0.7133 & 0.6474 & 0.5505 & 0.7840 & 0.1896 \\ 0.3826 & 0.7699 & 0.5716 & 1.0000 & 0.2368 \\ 1.0000 & 0.6038 & 0.3666 & 0.7739 & 0.3089 \\ 0.9069 & 0.6368 & 0.4462 & 0.8714 & 0.4328 \end{bmatrix}$$

Step 9: The weighted standardized decision matrix V is found by using Eq. (11) and presented below.

$$f_{ij} = \begin{bmatrix} 0.0549 & 0.2524 & 0.2524 & 0.1879 & 0.2524 \\ 0.1642 & 0.2417 & 0.2503 & 0.1420 & 0.2019 \\ 0.1586 & 0.2635 & 0.2450 & 0.1928 & 0.1402 \\ 0.2177 & 0.1780 & 0.3099 & 0.2043 & 0.0901 \\ 0.2473 & 0.2244 & 0.1908 & 0.2718 & 0.0657 \\ 0.1292 & 0.2600 & 0.1930 & 0.3377 & 0.0800 \\ 0.3275 & 0.1977 & 0.1201 & 0.2535 & 0.1012 \\ 0.2753 & 0.1933 & 0.1355 & 0.2645 & 0.1314 \end{bmatrix}$$

Table 13
Normalized decision matrix.

Alternative	U^-	U^+	$f(U^+)$	$f(U^-)$	AS	Ranking
$\mathfrak{Al}_1$	0.5460	0.5764	0.5135	0.4865	0.5613	6
$\mathfrak{Al}_2$	0.6309	0.6715	0.5156	0.4844	0.6514	3
$\mathfrak{Al}_3$	0.5136	0.5468	0.5157	0.4843	0.5304	7
$\mathfrak{Al}_4$	0.4780	0.5176	0.5199	0.4801	0.4981	8
$\mathfrak{Al}_5$	0.6075	0.6423	0.5139	0.4861	0.6251	4
$\mathfrak{Al}_6$	0.5519	0.5821	0.5133	0.4867	0.5671	5
$\mathfrak{Al}_7$	0.6498	0.6971	0.5176	0.4824	0.6737	2
$\mathfrak{Al}_8$	0.6673	0.7226	0.5199	0.4801	0.6953	1

$$V_{ij} = \begin{bmatrix} 0.3220 & 0.2338 & 0.1802 & 0.2039 & 0.0600 \\ 0.3513 & 0.2263 & 0.1760 & 0.1906 & 0.0558 \\ 0.3463 & 0.2293 & 0.1735 & 0.1988 & 0.0520 \\ 0.3625 & 0.2077 & 0.1827 & 0.1983 & 0.0488 \\ 0.3686 & 0.2148 & 0.1601 & 0.2095 & 0.0470 \\ 0.3335 & 0.2266 & 0.1634 & 0.2279 & 0.0486 \\ 0.3946 & 0.2066 & 0.1474 & 0.2032 & 0.0482 \\ 0.3802 & 0.2088 & 0.1519 & 0.2086 & 0.0504 \end{bmatrix}$$

Step 10, 11 and 12: The utility degrees for the ideal, anti-ideal solutions and utility functions are represented in Table 13. The appraisal scores of the alternatives are calculated by using Eq. (13) with the parameter $\delta = 0.5$. The graphical representation is shown in Fig. 6. The best alternative is $\mathfrak{Al}_8$.

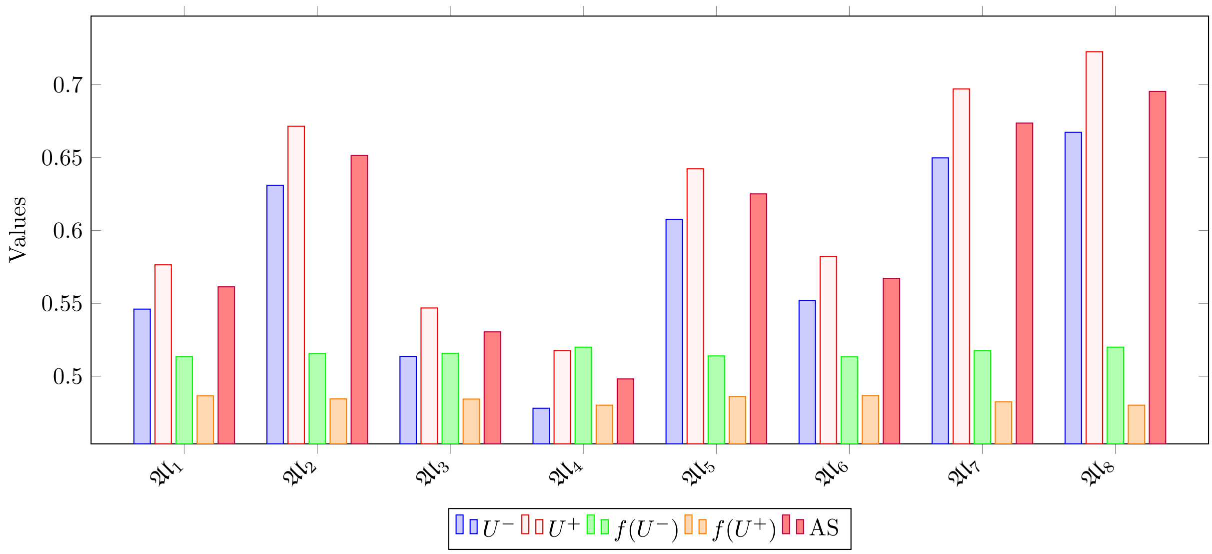

Fig. 6. Graphical representation of appraisal score.

Table 14
The impact of the parameter k and δ on the decision result.

δ	k	$\mathfrak{R}(\mathfrak{Al}_1)$	$\mathfrak{R}(\mathfrak{Al}_2)$	$\mathfrak{R}(\mathfrak{Al}_3)$	$\mathfrak{R}(\mathfrak{Al}_4)$	$\mathfrak{R}(\mathfrak{Al}_5)$	$\mathfrak{R}(\mathfrak{Al}_6)$	$\mathfrak{R}(\mathfrak{Al}_7)$	$\mathfrak{R}(\mathfrak{Al}_8)$	Ranking
$\delta = 0.1$	$k = 0.5$	0.5679	0.6259	0.5089	0.4763	0.6033	0.5616	0.6557	0.6663	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 1$	0.5491	0.6351	0.5170	0.4821	0.6111	0.5550	0.6546	0.6729	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 7$	0.5307	0.6434	0.5244	0.4873	0.6175	0.5493	0.6534	0.6788	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 50$	0.5279	0.6446	0.5255	0.4881	0.6184	0.5486	0.6532	0.6796	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 500$	0.5275	0.6448	0.5256	0.4882	0.6185	0.5484	0.6532	0.6797	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
$\delta = 0.3$	$k = 0.5$	0.5775	0.6377	0.5188	0.4873	0.6139	0.5711	0.6699	0.6817	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 1$	0.5552	0.6433	0.5237	0.4901	0.6181	0.5611	0.6642	0.6842	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 7$	0.5345	0.6485	0.5283	0.4928	0.6214	0.5527	0.6591	0.6864	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 50$	0.5314	0.6492	0.5290	0.4933	0.6219	0.5516	0.6583	0.6868	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 500$	0.5309	0.6493	0.5291	0.4933	0.6219	0.5514	0.6582	0.6868	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
$\delta = 0.5$	$k = 0.5$	0.5869	0.6495	0.5285	0.4981	0.6244	0.5805	0.6840	0.6968	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 1$	0.5613	0.6514	0.5304	0.4981	0.6251	0.5671	0.6737	0.6953	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 7$	0.5383	0.6535	0.5323	0.4983	0.6253	0.5561	0.6647	0.6940	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 50$	0.5349	0.6538	0.5326	0.4983	0.6253	0.5546	0.6634	0.6938	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 500$	0.5239	0.6247	0.5142	0.4814	0.6015	0.5491	0.6452	0.6821	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
$\delta = 0.8$	$k = 0.5$	0.5834	0.6481	0.5327	0.4999	0.6225	0.5763	0.6821	0.6934	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 1$	0.5601	0.6506	0.5315	0.4977	0.6247	0.5642	0.6705	0.6912	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 7$	0.5375	0.6528	0.5338	0.4985	0.6242	0.5578	0.6623	0.6907	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 50$	0.5338	0.6532	0.5316	0.4965	0.6236	0.5551	0.6607	0.6899	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
	$k = 500$	0.5242	0.6234	0.5126	0.4807	0.6004	0.5485	0.6437	0.6810	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$

4. Sensitive analysis

The analysis Table 14 and Fig. 7 demonstrate the complex relationship between parameters k and δ in our decision-making system. Increasing k tends to reduce individual scores marginally, indicating a greater emphasis on certain criteria, while maintaining a remarkably constant ranking order of alternatives throughout a wide range of 0.5 to 500. Elevating δ improves scores by relaxing choice constraints while maintaining a consistent ranking of alternatives. This robustness demonstrates the method's consistency in selecting the ideal alternative, which is critical for decision-making under changing situations. Furthermore, the method's computational efficiency is clear since parameter changes have little effect on ranking results, ensuring speedy and reliable decision support ideal for dynamic contexts and huge datasets. Future studies could look into adaptive parameter techniques that are suited to certain datasets or decision contexts, which would improve the method's adaptability and performance in a variety of decision-making settings.

4.1. Comparative analysis

The comparative analysis of our proposed LOPCOW-ERUNS with existing approaches in terms of stability, accuracy, and computing efficiency is shown in Table 15. Our approach reliably finds the best option for k and δ in a variety of circumstances, whereas traditional methods show notable variations in rankings when parameters are changed. Additionally, the LOPCOW-ERUNS approach maintains stability and accuracy in contrast to some other systems that exhibit fluctuations in rankings, indicating its superior performance in scenarios involving decision-making. These results highlight the usefulness of our approach, which makes it an effective tool for a range of applications needing accurate and reliable alternative selection.

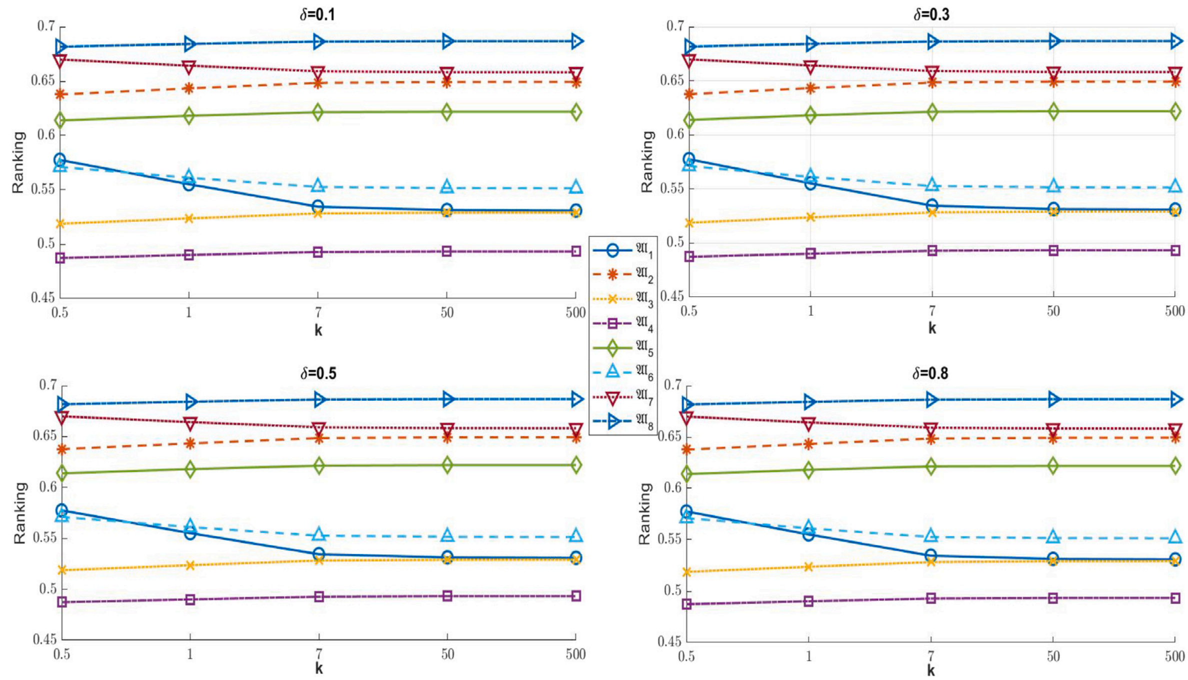

Fig. 7. Impact of δ and k on ranking.

Table 15
Comparison with newly proposed methods.

Authors	Methods	Ranking of alternatives
Iampan et al. [40]	LDFEWA and LDFEWG	$\mathfrak{Al}_7 \succ \mathfrak{Al}_8 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_4 \succ \mathfrak{Al}_3$
Aydoğdu et al. [41]	LDF-ARAS	$\mathfrak{Al}_8 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
Gül and Aydoğdu [42]	LDF-TOPSIS	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
Ayub et al. [43]	LD-FRS	$\mathfrak{Al}_8 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4 \succ \mathfrak{Al}_6$
Riaz et al. [44]	SLDFWAA and SLDFWGA	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
Aydoğdu [45]	Extended LDF-VIKOR	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
Kannan et al. [46]	LDF-DEMATEL	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$
Proposed	LOPCOW-ERUNS	$\mathfrak{Al}_8 \succ \mathfrak{Al}_7 \succ \mathfrak{Al}_2 \succ \mathfrak{Al}_5 \succ \mathfrak{Al}_1 \succ \mathfrak{Al}_6 \succ \mathfrak{Al}_3 \succ \mathfrak{Al}_4$

4.2. Managerial limitations

While the proposed decision-making framework offers a comprehensive and systematic approach to evaluating RE alternatives, several managerial limitations must be considered. Firstly, the accuracy of the framework heavily relies on the availability and quality of data for each criterion. Inaccurate or incomplete data can lead to suboptimal decision-making. Additionally, the integration of multiple advanced methodologies requires a high level of expertise and understanding, which may pose challenges for managers who are not familiar with these techniques. Although the framework aims to be objective, the initial selection and reduction of criteria involve subjective judgement, introducing potential bias into the decision-making process. Scalability is another concern, as the framework is designed for a specific case study with a defined set of criteria and alternatives. Adapting it to different contexts or larger scales may require significant modifications and additional resources. The dynamic nature of the RE sector, with continuous advancements in technology and changes in regulatory policies, necessitates frequent updates to keep the framework relevant and effective. Moreover, effective implementation requires active engagement and collaboration with various stakeholders, including government agencies, local communities, and industry experts, which can be challenging and time-consuming. Lastly, the comprehensive evaluation process may demand substantial financial and human resources, which may not be readily available, particularly in smaller municipalities or organizations with limited budgets. By acknowledging these limitations, managers can better prepare to address potential challenges and enhance the effectiveness of the decision-making process in selecting RE for Shenzhen. The findings of this study extend beyond methodological robustness, offering significant implications for policy development. The emphasis on solar thermal energy, despite its minimal representation in existing local energy portfolios, suggests a potential for strategic adjustment in RE policies. Aligning incentive schemes and spatial planning policies with these findings enables local governments to promote sustainable and publicly accepted energy transitions. The findings support global decarbonization objectives and highlight the need for localized policy innovations suited to high-density urban environments like Shenzhen.

5. Discussion of methodological and practical insights

This study comes up with a new way to make decisions by combining the LOPCOW-ERUNS method with the LiDFSMA aggregation operator. This makes it easier to deal with the uncertainties and complexities in MCDM. ERUNS, a new method for finding the best alternative, uses LOPCOW for objective weight determination and the LiDFSWA operator to aggregate decision-maker information. We validated the robustness and superiority of our suggested method by doing sensitivity and comparison analyses, demonstrating its resilience and reliability under diverse settings. The findings confirm that the LOPCOW-ERUNS approach, when supplemented with the LiDFSWA aggregation operator, greatly improves decision-making accuracy and consistency. The following is an outline of the primary benefits of this research article.

- This study shows a better and more advanced way to compare and choose the best option from several by using both quantitative and qualitative criteria together. It does this by combining the LOPCOW-ERUNS approach with the LiDFSWA aggregation operator.
- The implementation of RFE significantly simplifies the decision-making process by reducing the initial set of 14 criteria to the top five most influential ones, thereby guaranteeing a concentrated and comprehensive evaluation.
- To make the decision-making framework methodical, transparent, and replicable, a complete code of the process is developed. The pseudocode explains the technique and makes the framework practical and adaptable to suit different circumstances.
- The integration of LOPCOW ensures that the objective weights of criteria are precisely computed, whereas the ERUNS technique allows for a full and balanced examination, resulting in more informed and well-rounded conclusions.
- The case study highlights the practical importance of the framework by providing specific and concrete recommendations for RE planning in Shenzhen, aligned with sustainability goals.
- The sensitivity and comparative studies confirm the robustness of the proposed method, demonstrating its resilience under changing conditions as well as its capacity to deliver consistent and dependable results.

6. Conclusion

This research presents a hybrid decision-making framework aimed at identifying optimal RE sources in an uncertainty scenario, validated by a case study conducted in Shenzhen, China. The findings indicate that solar thermal power is the most appropriate alternative due to its efficiency, reliability, and alignment with the environmental conditions of the region. The combined application of RFE, LOPCOW-ERUNS and the LiDFSMA operator improves transparency, reduces complexity, and facilitates objective and replicable decision-making. The findings suggest that there are specific policy incentives, infrastructure improvements, and regulatory assistance to promote the adoption of solar thermal energy. The adaptability of the framework enables its application in various urban contexts, serving as a practical tool for sustainable energy planning. This resource is valuable for policymakers and urban planners who want to develop data-informed strategies for global RE transitions.

6.1. Future directions

Future directions can extend the proposed LOPCOW-ERUNS framework by exploring its applicability to broader domains such as urban planning, healthcare and transportation to validate its adaptability in diverse decision-making contexts. Future research should investigate the impact of regional regulatory constraints, socio-political factors, and economic disparities on decision outcomes within the framework of RE planning. Additionally, integrating dynamic stakeholder preferences through advanced techniques could provide personalized and context-sensitive evaluations. The existing model presumes unchanging stakeholder input and uniformity in expert judgement, thereby constraining its responsiveness to dynamic policy and community requirements. Addressing this limitation may be accomplished through the integration of learning-based systems or participatory modelling techniques. The development of user-friendly codes and software tools to automate the framework and visualize results would facilitate its adoption in practical scenarios. A modular, open-source implementation would enable researchers and policy analysts to customize and scale the tool according to country-specific datasets and energy policies. Finally, real-world implementations and pilot studies would provide practical validation and help refine the framework for enhanced decision-making accuracy in real-world scenarios. Future studies should incorporate cross-country case comparisons and longitudinal assessments to assess the model's consistency and policy relevance over time and across different geopolitical contexts.

CRediT authorship contribution statement

Muhammad Riaz: Writing – review & editing, Formal analysis, Data curation, Conceptualization. **José Carlos R. Alcantud:** Supervision, Methodology, Investigation. **Yasir Yasin:** Writing – original draft, Methodology, Investigation, Data curation. **Toqeer Jameel:** Investigation, Formal analysis, Data curation.

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.

Acknowledgment

Alcantud is grateful to the Department of Education of the Junta de Castilla y León and FEDER Funds (Reference: CLU-2025-2-03).

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