A novel multilevel decision-making evaluation approach for the renewable energy heating systems: a case study in China

Xueqing Yang[1], Xuejing Zheng [1, 3], Zhihua Zhou [1, 2], Hongfei Miao [1], Huzhen Liu [1], Yaran Wang [1, 3*], Huan Zhang [1, 3], Shijun You [1, 3], Shen Wei[4]

1 = *School of Environmental Science and Engineering, Tianjin University, Tianjin 300350, China*

2 = *Tianjin Key Laboratory of Indoor Air Environmental Quality Control, Ministry of Education of China, Tianjin 300350, PR China*

3 = *Key Laboratory of Efficient Utilization of Low and Medium Grade Energy (Tianjin university), Ministry of Education of China, Tianjin 300350, PR China*

4 = *The Bartlett School of Sustainable Construction, University College London (UCL), 1-19 Torrington Place, London, WC1E 7HB, United Kingdom*

* Corresponding author. School of Environmental Science and Engineering, Tianjin University, Tianjin 300350, China.

Abstract

Renewable energy (RE) sources are important alternatives to mitigate the energy crisis and achieve sustainable development. Appropriate selection of RE system solutions is extremely crucial. Selection of the best RE technology requires the consideration of conflicting qualitative and quantitative evaluation criteria. Many evaluation criteria are judged with subjectivity and uncertainty. However, the description of uncertainty in the evaluation process remains a large research gap. Therefore, a novel combined evaluation method is developed to describe and visualize the uncertainty in the assessment process. The proposed evaluation method is tested for RE heating system selection. The RE systems are evaluated based on five dimensions and 15 evaluation indicators. This multidimensional indicator framework not only includes the three basic evaluation groups of energy, economy, and environment, but also extends to the performance of technology and policy. The combined weights of the evaluation indicators consist of objective weights and subjective weights. The objective weights are obtained by the Criteria Importance Through Intercriteria Correlation (CRITIC) method and subjective weights are calculated by the improved Fuzzy Analytic Hierarchy Process (FAHP). The set pair analysis (SPA) is introduced to assess the performance of different RE systems. It considers the uncertainty of indicator performance. A novel approach to visualizing the fuzziness of SPA evaluation is developed using the cloud model. Finally, the RE system ranking calculated by the proposed method is performed. The originality of this work is offering a promising

method for RE selection and clarifying the degree of ambiguity in the evaluation process. It helps decision makers have an exact idea about the accuracy of the evaluation. It provides insights into multi-objective decision-making problems.

Highlights

- ✓ A multidimensional evaluation framework for renewable heating systems is proposed.
- ✓ The integrated weights of the criteria are obtained by the CRITIC and FAHP method.
- ✓ The ranking of the renewable heating systems is obtained by set pair analysis.
- ✓ Uncertainties in the evaluation process are described and visualized by cloud model.

Keywords

Evaluation method; Uncertainty visualization; Renewable energy; Combined weights; Set pair analysis; Cloud model

Word count

8361 words

Nomenclature

Q	Fuzzy complementary matrix (-)	Abbreviations	
r_{ij}	Relative importance of the ith indicator compared to the jth indicator (-)	RE	Renewable energy
X	Decision matrix (-)	CRITIC	Criteria Importance Through Intercrieria Correlation
ρ_{jk}	Correlation coefficient of jth and kth attributes (-)	FAHP	Fuzzy Analytic Hierarchy Process
C_j	Amount of information for the jth attribute (-)	SPA	Set pair analysis
σ_j	Standard deviation of the jth attribute (-)	DEA	Data Envelopment Analysis
ω_j	Weight of the jth attribute (-)	ANP	Analytic Network Process
μ	Connection degree (-)	TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
Ex	Expectation (-)	GRA	Grey Relation Analysis
En	Entropy (-)	AHP	Analytic Hierarchy Process
He	Hyper-entropy (-)	VIKOR	Vlsekriterijumska Optimizacija I KOmpromisno Resenje
γ	Certainty degree (-)	EWM	Entropy weight method
S_i	Comprehensive score of each system (-)	PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
$\widehat{\omega}_j$	Combination weight of the jth criterion (-)	DEMATEL	Decision-making Trial and Evaluation Laboratory
$\widehat{\omega}_{ij}$	Weight of the jth indicator with respect to the ith system (-)	ELECTRE	Elimination and Choice Translating Reality
D_i^+	Distance of alternatives to the positive ideal solution (-)	RES	Renewable energy source
D_i^-	Distance of alternatives to the negative ideal solution (-)		
c_i	Relative closeness coefficient (-)		

1 Introduction

Recent years have witnessed the rapid growth of the world economy and the attendant energy consumption issues (Yu, Y. et al., 2019). The structure of energy consumption plays an essential role in energy security and the well-being of the population. In rural China, residents rely mainly on poor quality coal and traditional biomass (Han and Wu, 2018). It intensifies CO_2 emissions and triggers increasingly critical social and environmental issues. The progressive replacement of fossil fuels with renewable energy (RE) is considered the most widely endorsed answer to pursue building decarbonization and climate protection (Aloini et al., 2021; Gong et al., 2021). How to evaluate the best RE project efficiently is a strategic and significant problem that decision makers need to face (Zheng et al., 2022).

The evaluation methods of RE systems are constantly being explored since the multidimensional criteria involve occasionally conflict with each other (Rani et al., 2019). Evaluation criteria are often assigned weights to rank alternatives (Büyüközkan and Güleryüz, 2016). To ensure the integrity of the evaluation, subjective indicators with uncertainty caused by expert judgement are often introduced. The uncertainty associated with the subjective data cannot be properly measured. There is a research gap regarding the description of fuzziness in assessment. The fuzziness comes from the subjective preferences of experts in weighting judgements and system performance judgements. In this paper, a novel method for associating set pair analysis (SPA) with cloud models is developed to visualize the fuzziness involved in the evaluation process.

It allows decision makers to better judge the accuracy of the evaluation results by visualizing the ambiguity.

The combined weights of the evaluation criteria include both objective and subjective weights. Subjective weights are determined by the improved Fuzzy Analytic Hierarchy Process (FAHP), and objective weights are calculated by the Criteria Importance Through Intercrieria Correlation (CRITIC) method. The application of FAHP introduces uncertainty to the evaluation. The set pair analysis proposed by Zhao (Aili, 1996) is a theoretical method to deal with uncertainty problems. It can effectively demonstrate the ambiguity of expert judgment on qualitative concepts. Over the last few decades, the SPA method has been successfully applied in multi-attribute decision-making (Garg and Kumar, 2019; Kumar and Chen, 2021).

The cloud model is a cognitive model that studies the uncertainty transformation between qualitative and quantitative concepts (Wu et al., 2020). Considering the exceptional performance of the cloud model in handling linguistic information with uncertainty, it is obvious that it can be a strong option for solving ambiguity evaluation problems. The cloud model demonstrates the ambiguity by the cloud droplet figure. The greater the ambiguity, the more dispersed the cloud droplets. The evaluation results are identified by comparing the alternative cloud with the evaluation grade cloud. The cloud model is widely used in the field of uncertainty evaluation (Guo et al., 2016; Liu et al., 2019; Zhao and Li, 2015).

The proposed evaluation framework is superior to existing methods in the following aspects:

(1) The combined weights consist of subjective weights calculated by the improved FAHP and objective weights obtained by the CRITIC method. It can embody both the experience of decision makers and the information from the indicator data.

(2) The SPA method is applied to scoring and ranking the different scenarios. It considers the uncertainties of the level to which the scenario performance belongs.

(3) Correspond the SPA results to the cloud model numerical characteristics. Cloud droplet figures are displayed to demonstrate the ambiguity of the evaluation process and the dispersion of indicator levels.

In this paper, a novel evaluation model is proposed and applied to the selection of RE heating systems. Solar, biomass and geothermal energy are discussed as they are commonly used for heating (Cansino et al., 2011; Zheng et al., 2022). Five RE heating systems are selected to be evaluated and ranked in terms of economic, technical, environmental, social and resource criteria. The remainder of the paper is structured as follows: Section 2 briefly reviews the existing literature. Section 3 specifies the evaluation framework of RE systems, outlines the research methodology and illustrates the data sources. In section 4, the application of the proposed approach and the results are presented. Section 5 validates and discusses the results. In addition, policy recommendations are provided. The key conclusions are drawn out in section 6. Finally, section 7 describes the limitations of the study and future recommendations.

2 Literature review

In recent years, scholars have carried out further research on approaches to selecting appropriate RE projects. The RE project evaluation methods include attribute weighting and programme ranking.

The determination of attribute weight is acknowledged as a critical step in multi-criteria decision making (MCDM) (Gong et al., 2021). Classical weighting methods include Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Entropy Weight Method (EWM) and Criteria Importance Through Intercriteria Correlation (CRITIC) method (Çelikbilek and Tüysüz, 2016).

Some studies have employed the AHP and ANP methods. The determination of indicator weight requires subjective assessment by experts. (Karakas and Yildiran, 2019) proposed modified FAHP to assess the performance of hydro, wind, solar, biomass and geothermal energy in Turkey. Turkey is an energy importing country and air pollution is becoming a great environmental concern. Renewable energy sources (RESs) appear to be one of the most effective solutions for sustainable energy development. The alternatives were assessed in light of technical, economic, environmental and social criteria. The finding demonstrated that solar energy was the best alternative. (Mastrocinque et al., 2020) provided an MCDM framework based on the Triple Bottom Line principles and AHP methodology for sustainable supply chain development in the RE sector. RE electricity generation is beginning to play an important role in European countries. This study compared main European countries producers of PV energy. The evaluation framework was based on the three Triple Bottom Line dimensions such as social, economic and environmental. They concluded that Germany represented the highest rated alternative, while UK and Belgium were the lowest. The ANP method was introduced by (Yu, S. et al., 2019) to evaluate regional RE development in China based on energy, economic, environmental, technological and social performance. Improving the level of the RE utilization and reducing the abandonment rate of wind power and photovoltaic power are important challenges faced by China. They concluded that Qinghai ranked the top in RE development performance out of 30 provinces. The improved AHP and ANP method applied in the above studies have improved the applicability of the evaluation to some extent. However, it still inevitably introduced the subjective knowledge of experts and failed to capture the degree of uncertainty.

Some studies applied a completely objective approach to identify indicator weights. The impact of the emission trading scheme on RE was studied by (Lin and Jia, 2020) using EWM. The economic, environmental and social performance of eight scenarios were compared. Their work showed that emission trading schemes with no subsidy for renewable would reduce the demand for energy and increase the cost of RESs. (Asante et al., 2022) assessed RE barriers and prioritized RE adoption strategies in Ghana. The current electricity mix in Ghana is relatively unclean, and it continues to suffer perennial erratic power supply. The country's energy bill aimed at developing abundant RE sources (solar, mini-hydro, geothermal, and biogas) to address the dilemma. Twenty-two barriers were identified and weighted by the CRITIC method. The findings suggested that the severity of the main barriers facing Ghana's RE development follows the order of technical, economic and financing, political and regulatory, institutional, social, and geographical barriers. The objective weighting method avoids subjectivity. However, it may cause bias in the results because it is based on data information alone.

Typical programme ranking methods involve the Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR), Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), Grey Relation Analysis (GRA), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Decision-making Trial and Evaluation Laboratory (DEMATEL) and Elimination and Choice Translating Reality (ELECTRE). A four remoteness index-based VIKOR method was developed by (Khan et al., 2020) to select RESs in under developing countries. (Davoudabadi et al., 2021) improved DEA to find outstanding energy projects. Moreover, a combination of the above methods has been applied by several scholars for comprehensive evaluation. Fuzzy AHP and the GRA approach were integrated by (Ayağ and Samanlioglu, 2020) to evaluate a set of potential energy sources. The proposed approach showed strong practicality for potential practitioners who are experts in the field of energy in public and private sectors. (Erdin and Ozkaya, 2019) conducted the AHP-ELECTRE method to select the site and decide appropriate RESs. The most suitable energy sources in Turkey were presented according to geography and energy potential. (Li et al., 2020) introduced the ANP method to evaluate the importance of each criterion. In addition, MCDM methods such as TOPSIS, PROMETHEE, ELECTRE and VIKOR were used to rank RE alternatives so that different methods could support each other to make the results more convincing. Likewise, the CRITIC technique combined with the TOPSIS technique were utilized to determine the hybrid RES for a rural community (Babatunde and Ighravwe, 2019). The descriptions and applications of different approaches employed in well-documented literature are presented in Table 1.

In summary, the existing literature covers extensive research on RE MCDM methods. For a comprehensive evaluation, subjectivity and uncertainty are tended to be introduced caused by expert judgment. However, there remains a largely unaddressed scientific gap in describing and visualizing ambiguity. It may mislead decision makers from properly assessing the accuracy and validity of decisions. Therefore, this study incorporates SPA with cloud models to effectively describe and visualize uncertainty and ambiguity. Besides, the decision-making issue of RE for heating is rarely discussed even though it is gaining momentum. In this study, a holistic and integrated assessment process for RE heating is proposed and applied, laying the foundation for the development of RESs.

Table 1 Summary of the main evaluation methods for RE selection.

References	Methods	Method description	Application
(Mastrocinque et al., 2020)	AHP	Pairwise comparison based method Simple and practical Weights are determined with subjectivity	Providing decision makers with the main factors of RE development.
(Şengül et al., 2015)	EWM-TOPSIS	Weights are determined objectively (EWM) Ranking by detecting the distance of the evaluation object from the best and worst solutions (TOPSIS)	Ranking RE Supply Systems.
(Khan et al., 2020)	VIKOR	Maximizing group benefits and minimizing individual regrets of objections Weights are determined objectively	Selecting the most appropriate RE projects.
(Davoudabadi et al., 2021)	Data Envelopment Analysis (DEA)	Relative effectiveness evaluation based on multiple input and multiple output indicators	Selecting the most appropriate RE projects.
(Ayağ and Samanlioglu, 2020)	Fuzzy AHP-GRA	Weights are determined with subjectivity (AHP) Ranking the scenarios according to the degree of correlation between the highest score and the score for each factor (GRA)	Selecting energy source in Turkey.
(Erdin and Ozkaya, 2019)	AHP-ELECTRE	Weights are determined with subjectivity (AHP) Outranking methods by constructing a series of weak dominance relationships to eliminate poor solutions	Determining the sites of RE construction.
(Büyüközkan and Güleryüz, 2016)	ANP-DEMATEL	Weights are determined with subjectivity (ANP) Constructing interrelations between criteria and finding the central criteria that represent the effectiveness of factors (DEMATEL)	Selecting the most appropriate RE from an investor-focused perspective.
(Li et al., 2020)	ANP-PROMETHEE	Weights are determined with subjectivity (ANP) Outranking methods by performing a pair-wise comparison (PROMETHEE)	Identifying priorities for RE in different regions of China.
(Babatunde and Ighravwe, 2019)	CRITIC-TOPSIS	Weights are determined objectively based on contrast intensity and the conflicting character of the evaluation criteria (CRITIC)	Selecting a hybrid model for RE electricity generation.

3 Methodology

A novel evaluation approach combining SPA with the cloud model is developed and employed in RE system selection. RE heating systems are assessed based on economic, technical, environmental, social and resource criteria. Evaluation indicators are attributed subjective weights by the improved FAHP method and assigned objective weights by the CRITIC method. Subsequently, the subjective and objective weights are synthesized using genetic algorithms. Given the inaccuracy of the evaluation data (especially for qualitative criteria), the SPA method is applied to resolve the uncertainty in the evaluation process of prioritizing RE systems. A novel cloud model is developed to visualize the fuzziness in SPA evaluation. As a result, the uncertainty in assessment process is effectively characterized. It helps decision makers more accurately determine the ranking of alternatives and clearly identify the degree of uncertainty in the evaluation process. The structure of the proposed evaluation process is given in Fig. 1.

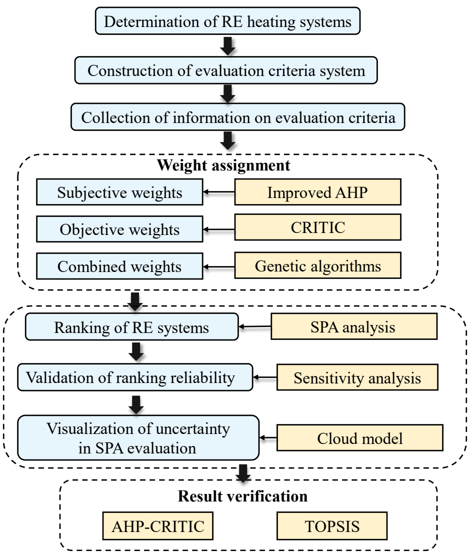


Fig. 1. Proposed evaluation framework.

3.1 The studied RE heating systems

Solar, geothermal and biomass energy are commonly used for heating to reduce the pressure on fossil fuel. In this paper, five promising RE heating systems are discussed below.

a) Shallow ground source heat pump

Shallow geothermal energy (< 400 m depth) is mainly used for low-moderate temperature heating and cooling. It is often combined with heat pumps to transfer low-temperature thermal energy to high temperature by consuming electric power. But attention needs to be paid that the heat balance should be maintained between heating in winter and cooling in summer.

b) Solar collectors

Solar thermal systems have developed into a mature and economically feasible technology due to the cleanest and inexhaustible of solar energy. Apart from the high initial investment in equipment, the major problem is that solar energy is discontinuous and unstable, which leads to low heating efficiency in poor weather conditions. For more reliable and efficient heating, large solar collector panels and high-volume thermal storage tanks are indispensably required.

c) Household biomass boilers

Biomass is one of the earliest energy sources derived from plant and animal material. It is widely used in rural areas where it is affordable and readily available. An effective way of using biomass energy is to extrude crushed agricultural waste, forestry waste and straw into lumpy fuels for combustion in biomass boilers. Meanwhile, the straw ash produced by the burning of biomass can provide fertilizer for agricultural production and resources are recycled.

d) Solar-ground source heat pump hybrid system

Given the low operating costs but the unreliability of solar energy, it is combined with ground source heat pumps to form a "decentralized + central heating" model. The heating load carried by the solar system is allocated according to the local solar fraction. Heating schemes using RES combinations are economic and environmentally friendly models that have been strongly promoted by the government. But most research is currently at a theoretical level and not yet mature enough.

e) Solar-household biomass boilers hybrid system

Solar-household biomass boilers hybrid system make full use of the respective advantages of biomass and solar energy. It not only reduces the use of biomass fuel and extends the service life of biomass boilers, but also compensates for the instability of solar energy. The system has a strong complementary and extensive promotion value.

3.2 Framework of evaluation criteria

Renewable energy heating, an input-output production system involving exploration, development, operation and consumption, inevitably needs to be judged by multi-dimensional criteria (Zhang et al., 2019). Due to different research focuses, scholars have evaluated different types of RE performance from different perspectives, including economic performance (Korsavi et al., 2018; Lehr et al., 2012), energy performance (Dong and Shi, 2019; Raugei and Leccisi, 2016), environmental performance (Adams and Acheampong, 2019; Dogan and Seker, 2016), technology performance (Henninger et al., 2017), and policy performance (Matsumoto et al., 2017; Pérez de Arce et al., 2016). Some studies have also assessed multiple performances of RE by using different methods (Amer and Daim, 2011; Atmaca and Basar, 2012). These studies are based on the application of multi-criteria methods for the selection of renewable electricity, power plant siting, or the RE policies. It has rarely been used to evaluate the performance of RE heating on a comprehensive scale. Moreover, this paper expands the indicators of user preferences and current utilization rate to reflect the local RE development more comprehensively. Therefore, the RES alternatives can be assessed against five main criteria and 15 sub-criteria shown in Fig. 2. Six criteria need to be judged by experts with subjectivity.

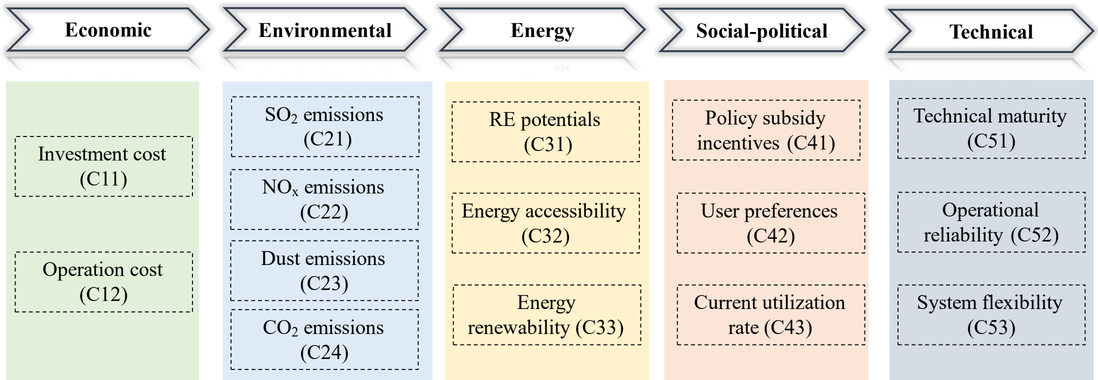


Fig. 2. Framework of evaluation criteria.

The data descriptions and access method of each criterion are shown in Table 2.

Table 2 Criteria descriptions and data access.

main criteria	sub-criteria	Description	Data type	Data access
Economic (C1)	Investment cost (RMB/m^2)	Cost occurred for establishing the system	Quantitative	Previous study (Administration, 2017)
	Operation cost (RMB/m^2)	Cost of running and maintaining the system		

Environmental (C2)	SO_2 emissions (g/m^2)	Emissions of pollutants from fuel combustion or equivalent emissions from electricity use	Quantitative	Calculation based on reference (Saidur et al., 2011; Wang et al., 2018)
	NO_x emissions (g/m^2)			
	Dust emissions (g/m^2)			
	CO_2 emissions (g/m^2)			
Energy (C3)	RE potentials (MJ)	Amount of RE resources	Quantitative	Calculation
	Energy accessibility	Degree of difficulty in accessing renewable energy	Qualitative	Expert assessments
	Energy renewability	Regeneration rate back to use level	Qualitative	Expert assessments
Social-political (C4)	Policy subsidy incentives	Local subsidy policy on RE for heating	Qualitative	Expert assessments
	User preferences (%)	Preferences of heating customers for each RE system	Quantitative	Questionnaires
	Current utilization rate (%)	Current development state of RE systems	Quantitative	Questionnaires
Technical (C5)	Technical maturity	Commercialization and economic accessibility of RE technologies	Qualitative	Expert assessments
	Operational reliability	Stability during system operation		
	System flexibility	System adjustability according to user requirements		

3.3 Analysis methods

3.3.1 The improved FAHP method

AHP is a multi-criteria decision making technique developed for solving selection, ranking and classification problems (Saaty, 1980). The method consists of an objective layer (an optimum RE System), a criterion layer (15 evaluation criteria) and an alternatives layer (five RE systems). The weights are determined by constructing pairwise comparison matrices based on the fuzzy numbers assessed by experts. The traditional five-scale 0 ~ 9 method adopted for AHP has low precision and is prone to failing consistency tests when there is a large amount of data. To overcome the issues, an improved FAHP method using five-scale 0.1 ~ 0.9 (Table 3) to construct a fuzzy consistent judgement matrix is employed to obtain subjective weights. The basic steps of the improved FAHP method are briefly described below (Wang and Guo, 2010).

Table 3 Measurement scale used by improved FAHP.

Scales	Interpretation (A compared to B)
0.1	B is extremely more important than A
0.3	B is obviously more important than A
0.5	A is equally important to B
0.7	A is obviously more important than B
0.9	A is extremely more important than B

Step 1: A hierarchical structure based on goal setting, criteria, sub-criteria, and alternatives is developed.

Step 2: The relative importance r_{ij} indicates the importance of the ith indicator compared to the jth indicator. It is judged according to Table 3.

Step 3: Construct the 0.1~0.9 fuzzy complementary matrix $Q = [r_{ij}]_{n\times n}$ that satisfies Eq. (1) according to experts' responses.

$$r_{ij} + r_{ji} = 1 \tag{1}$$

Step 4: Transform Q into a fuzzy consistency matrix and the weights of the criteria are calculated accordingly. The calculation flow chart is shown in Fig. 3.

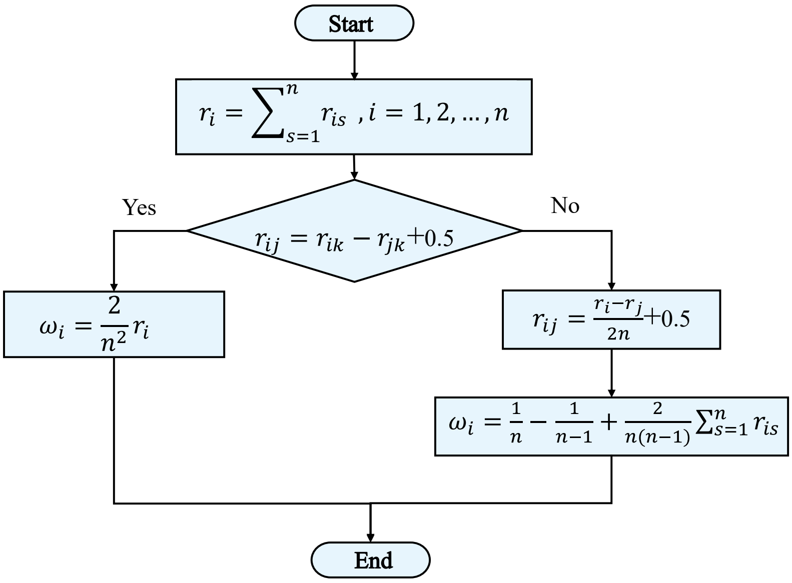


Fig. 3. Subjective weighting calculation flow chart.

3.3.2 The CRITIC method

The CRITIC method aims at determining the objective weights (Diakoulaki et al., 1995). The index weights are assigned based not only on the information of the indices but also on the correlation between them. It is a comprehensive and superior objective weighting method. The main steps are described as follows:

Step 1: The decision matrix X is established as Eq. (2) to show the performance of different RE systems.

$$X = [\, x_{ij} \,]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{2}$$

where i represents RE systems and j represents criteria.

Step 2: Normalize the positive and negative criteria of the decision matrix using Eqs. (3) and (4), respectively.

$$x'_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{3}$$

$$x'_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{4}$$

Step 3: Calculate the correlation coefficient among attributes according to Eq. (5):

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(x'_{ij} - \overline{x_j{}'}) - (x'_{ik} - \overline{x_k{}'})}{\sqrt{\sum_{i=1}^{m}(x'_{ij} - \overline{x_j{}'})^2 \sum_{i=1}^{m}(x'_{ik} - \overline{x_k{}'})^2}} \tag{5}$$

where $\overline{x_j}$ and $\overline{x_k}$ denote the mean of the *j*th and *k*th criteria, respectively.

Step 4: Determine the amount of information C_j by Eq. (6) which reflects the fluctuation and conflict of decision attributes.

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk}) \tag{6}$$

where σ_j is the standard deviation of the RE system performance at the *j*th criterion, as shown in Eq. (7):

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x'_{ij} - \overline{x_j{}'}\right)^2} \tag{7}$$

Step 5: The weight of the *j*th criterion can be given by Eq. (8):

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{8}$$

3.3.3 The SPA-Cloud model method

a) The SPA method

The SPA method defines objects and their interactions by “identity,” “discrepancy,” and “contrary” (Zhao, 1989). The core function of SPA is to analyze uncertainty problems quantitatively so that uncertainties in expert judgement can be dealt with effectively. Putting together set *A* and *B* to form set pair *H* regarding problem *W*. The method combines certainties with uncertainties as an integrated system by connection degree μ, as shown in Eq. (9) (Su et al., 2020).

$$\mu = \frac{S}{N} + \frac{F}{N}i + \frac{Z}{N}j \tag{9}$$

where N is the total number of characteristics between A and B, S represents the number of identity characteristics, P denotes the number of contrary characteristics, $F = N - S - P$ is the number of the characteristics that are neither identity nor contrary, S/N, F/N, and P/N, referred to the identity degree, the discrepancy degree, and the contradictory degree, respectively. $i \in [-1, 1]$ is the uncertainty coefficient of the discrepancy, j denotes the contradictory coefficient ($j = -1$).

As a modified form, the five-element connection number is more thoroughly used for uncertainty analysis. The connection degree of the pth criteria can be expressed as the form of Eq. (10):

$$\mu_p = R_{p1} + R_{p2}i_1 + R_{p3}i_2 + R_{p4}i_3 + R_{p5}j \quad (10)$$

It can be detailed as (Wang et al., 2016):

$$\mu_{pl} = \begin{cases} 0 + 0i_1 + 0i_2 + 0i_3 + 1j & x < S_1 \\ 0 + 0i_1 + 0i_2 + \frac{2x-2S_1}{S_2-S_1}i_3 + \frac{S_1+S_2-2x}{S_2-S_1}j & S_1 \leq x < \frac{S_1+S_2}{2} \\ 0 + 0i_1 + \frac{2x-S_1-S_2}{S_3-S_1}i_2 + \frac{S_3+S_2-2x}{S_3-S_1}i_3 + 0j & \frac{S_1+S_2}{2} \leq x < \frac{S_2+S_3}{2} \\ 0 + \frac{2x-S_3-S_2}{S_4-S_2}i_1 + \frac{S_4+S_3-2x}{S_4-S_2}i_2 + 0i_3 + 0j & \frac{S_2+S_3}{2} \leq x < \frac{S_3+S_4}{2} \\ \frac{2x-S_3-S_4}{S_4-S_3} + \frac{2S_4-2x}{S_4-S_3}i_1 + 0i_2 + 0i_3 + 0j & \frac{S_3+S_4}{2} \leq x < S_4 \\ 1 + 0i_1 + 0i_2 + 0i_3 + 0j & x \geq S_4 \end{cases} \quad (11)$$

where x is the evaluation indicator value, and S_1, S_2, S_3 and S_4 are the extreme values of each evaluation interval.

The connection degree μ of the alternative meets:

$$\mu = R_1 + R_2i_1 + R_3i_2 + R_4i_3 + R_5j \quad (12)$$

where $R_l = \sum_{p=1}^{m} \omega_p R_{pl}$, ($1 \leqslant p \leqslant m$, $1 \leqslant l \leqslant 5$), ω_p is the weight of the pth criteria. In this paper, j indicates that the RE system alternative performs worst under a given criterion, while i indicates that the alternative performs between the worst and best. i_1, i_2, i_3 are defined as 0.5, 0, -0.5, respectively, according to the equipartition principle.

b) Cloud model

Considering the randomness and fuzziness, (Deyi et al., 1995) proposed cloud models based on the probability theory and fuzzy theory. The ambiguity of decision information is captured through the distribution of cloud droplets generated by the cloud generator. The cloud generator is an intermediate converter between qualitative concepts and quantitative characteristics. It includes the forward cloud generator and reverse cloud generator. The forward cloud generator obtains quantitative information from qualitative linguistic information, while the reverse cloud generator can accomplish the transformation from quantitative features to qualitative notions.

The distribution of cloud droplets can be determined by three numerical parameters (Ex, En, He). The descriptions and calculation of the numerical characteristics for the cloud model are outlined in Table 4.

Table 4 Description and calculation of the numerical characteristics.

Parameter	Meaning	Description
Ex	Expectation	The best representation of concept quantization
En	Entropy	Randomness and vagueness measurements of the qualitative concept
He	Hyper-entropy	Uncertainty degree of entropy En

Ex represents the center value of the qualitative concept and determines the distribution location of a cloud drop. En is a randomness measure of the qualitative concept, which indicates the value range of a cloud drop expressed by the qualitative concept in the universe of discourse. In the cloud map, *He* usually indicates the thickness of the cloud. The larger the hyper-entropy, the thicker the cloud. The graphical implications of the numerical parameters are demonstrated in Fig. 4.

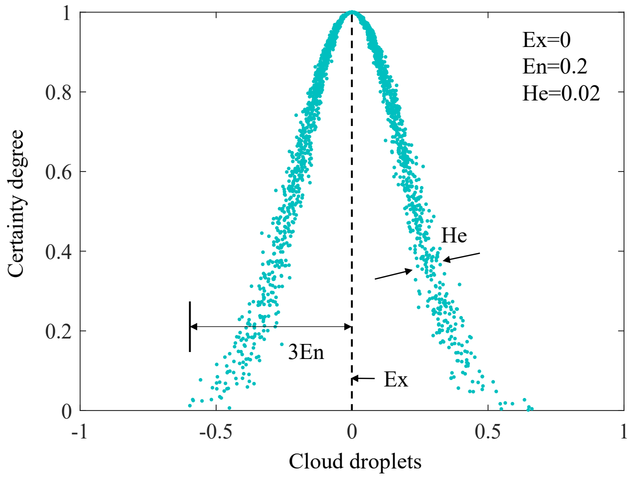


Fig. 4. graphical implications of the numerical parameter.

In this study, *Ex* refers to the score of the RE system calculated by SPA, and *En* as well as *He* can reflect the uncertainty degree of the evaluation.

The cloud model can be created by the following two phases:

Phase I: Determine the cloud numerical characteristics of each indicator level. For the form of an interval [B_{min}, B_{max}], the numerical parameters (*Ex*, *En*, *He*) can be derived as follows:

$$\begin{cases} Ex = (B_{min} + B_{max})/2 \\ En = (B_{max} - B_{min})/6 \\ He = kEn \end{cases} \tag{13}$$

where *k* is an adjustment coefficient to regulate the 'atomization' degree within the level cloud. Here, *k* is assumed as 0.1.

Compute the certainty degree γ by Eq. (14) and then obtain the forward clouds of different evaluation levels.

$$\gamma(x) = exp^{-\frac{(x-Ex)^2}{2En'^2}} \tag{14}$$

Where En' follows a normal distribution $En' \sim N(En, He^2)$.

Phase II: Determine the cloud numerical characteristics of each indicator sample. The evaluation indicator samples are treated as inputs in the reverse cloud generator to compute the cloud numerical characteristics of the samples.

c) Integration of the SPA method and cloud model

As noted above, both the SPA method and the cloud model can reflect the ambiguity degree. Connections between the two methods are established to visualize the ambiguity of the SPA assessment. The connection is found between the numerical parameters of the reverse cloud generator and the uncertainty degree μ of the SPA result. The expectation Ex is set to the value of μ.

En measures the degree of random dispersion of cloud droplets. As mentioned in Eq. (11), when $x \geqslant S_4$ and $x < S_1$, there is no ambiguity due to the identity and the contradictory degree being 1 and 0, respectively. When $S_1 \leqslant x < S_4$, x does not fall exactly within a certain evaluation interval, and two coefficients of R_i have assigned values. The smaller one is taken as the fuzziness measurement. The larger *En* is, the more ambiguous is the level of judgment on the performance x_{ij}. Thus, *En* can be derived as follows:

$$En = \begin{cases} 0 & x < S_1 \\ \sum_{j=1}^{n} \omega_j \times \min R_i & S_1 \leq x < S_4 \\ 0 & x \geq S_4 \end{cases} \tag{15}$$

where ω_j is the weight of the jth evaluation criterion.

He is the uncertainty degree of *En* and can be determined by the difference between the sample variance and En (Yao et al., 2019). The larger He is, the more inconsistent is the level of judgment on each index. As calculated in Eq. (12), the maximum of R_i is considered as the certainty of the evaluation process and the other four as the ambiguity. R_1, R_2, …, R_5 are arranged in ascending order as R_a, R_b, …, R_e. He is defined as Eq. (16)

$$He = |(R_a^2 + R_b^2 + R_c^2 + R_d^2) - En| \tag{16}$$

The calculation steps are described below. Steps 1 ~ 3 are based on the SPA method and steps 4 ~ 5 rely on the cloud model.

Step 1: The normalized decision matrix $X = [\, x'_{ij} \,]$ has been defined as in Eq. (2). In this paper, the evaluation criteria levels are divided into five categories: [0, 0.2), [0.2, 0.4), [0.4, 0.6), [0.6, 0.8), [0.8, 1]. i.e., the extremes of standards S_1, S_2, S_3, S_4 are 0.2, 0.4, 0.6 and 0.8, respectively. Therefore, the connection degree for each evaluation criterion can be calculated by Eq. (11).

Step 2: Determine the connection degree of the five RE systems using Eq. (12).

Step 3: Define i_1= 0.5, i_2 = 0, i_3 = -0.5, j = -1 and calculate the five-element connection number as the basis for ranking alternatives.

Step 4: Calculate the numerical characteristics of the evaluation interval and construct an evaluation cloud droplet figure. The scores (connection degree) generated by the SPA method (step 3) are divided into five categories: [-1, -0.6), [-0.6, -0.2), [-0.2, 0.2), [0.2, 0.6), [0.6, 1], corresponding to classes V, IV II, III, II, I, respectively. The corresponding certainty degree for each evaluation interval is worked out by Eq. (13)

and plotted as a cloud droplet figure.

Step 5: Compute the cloud numerical characteristics of each RE system. The calculations are accomplished using Eqs. (15) and (16). Comparison of the RE system cloud droplet figure with the evaluation cloud droplet figure allows visualization of the SPA method results.

The calculation process of the SPA-cloud model based method is shown in Fig. 5.

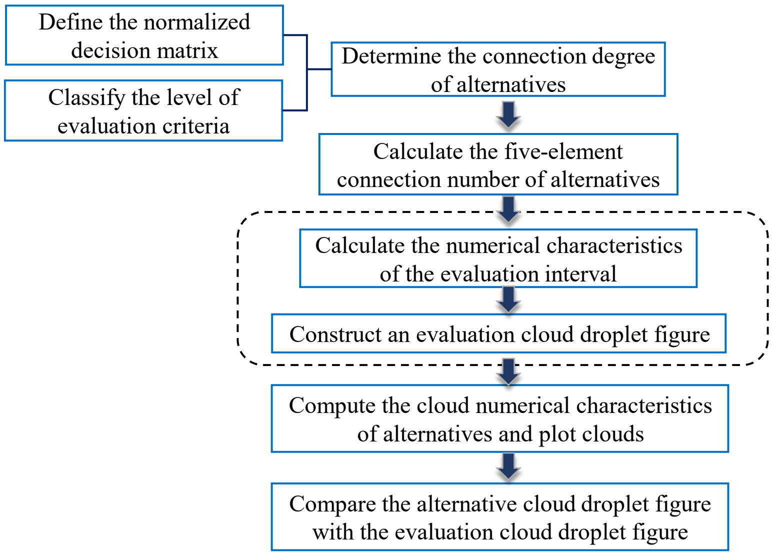


Fig.5 The calculation process of the SPA-cloud model based method.

3.4 Data source

As shown in Table 2, data information comes from previous studies, expert assessments, calculations and resident questionnaires. A professional questionnaire was prepared to solicit the opinion of 15 experienced academic experts and industrial experts majoring in renewable energy. Experts scored between 1 and 100 and the average of them was taken as the final performance results. User preferences and current utilization rate were derived from a questionnaire distributed to residents. RE heating potentials can be estimated using the method proposed by (Zheng et al., 2022).

4 Case study

In this section, the proposed method is applied to Pingtou Town in Shaanxi Province, China. Subjective weights are calculated by the improved FAHP method, objective weights are derived by the CRITIC method. A genetic algorithm is employed to obtain the integrated weights. Combined with the calculated criteria weights, the SPA and cloud models are applied to prioritize RE systems. A sensitivity analysis is conducted to verify the stability of the proposed model. Finally, the evaluation results of the five RE systems are determined and discussed. We use the analysis software python in our study. The genetic algorithm toolbox is used to calculate the combined weights. The normal function is employed to generate cloud graphs of the normal distribution.

4.1 Study area

To promote RE development more broadly, Pingtou Town, which has favorable policies and resources in northwest China, is selected for this study. It covers an area of 317 km^2 and contains a population of 20,210 currently (Office, 2021). Low building densities and open sites in rural areas are prerequisites for the development of RE technologies. Pingtou Town has carried out a photovoltaic poverty alleviation project, with superior agricultural conditions and robust policies for developing geothermal energy, making it a strong momentum for RE development. The method is adopted to assess the performance of the five RE systems in Pingtou Town.

4.2 Data preparation

The data received from experts, calculations, questionnaires and extensive literature reviews are aggregated in Table 5. It is obtained based on the latest policy changes, technological developments and research reports.

Table 5 Original data matrix.

System	Economic		Environmental				Energy			Social-political			Technical		
	C_{11} (RMB/m^2)	C_{12} (RMB/m^2)	C_{21} (g/m^2)	C_{22} (g/m^2)	C_{23} (g/m^2)	C_{24} (g/m^2)	C_{31} (MJ)	C_{32}	C_{33}	C_{41}	C_{42} (%)	C_{43} (%)	C_{51}	C_{52}	C_{53}
A	150	25	6.227	14.78	0.788	1933.7	6.32×10^5	60.4	81.4	93	36.67	10	74.3	92	53.2
B	350	10	0	0	0	0	2.53×10^7	97	96.4	77	33.33	56.67	93.7	42	88
C	50	25	2.379	5.791	2.873	5593.8	8.86×10^7	77.7	85.7	51.3	16.67	3.33	36.2	77	62.3
D	210	20.5	4.3589	10.346	0.5516	1353.59	8.05×10^6	78.8	84.6	70.2	46.67	2.4	54	70	81
E	140	20.5	1.6653	4.0537	2.0111	3915.66	6.9×10^7	93.4	91.2	57.2	40	1.2	16.6	79	82.4
Remark	A: Shallow ground source heat pump, B: Solar collectors, C: Household biomass boilers, D: Solar-ground source heat pump hybrid system, E: Solar-household biomass boilers hybrid system														

The normalized decision matrix is shown in Table 6:

Table 6 Normalized decision matrix.

System	Economic		Environmental				Energy			Social-political			Technical		
	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}
A	0.667	0	0	0	0.726	0.654	0	0	0	1	0.667	0.159	0.748	1	0
B	0	1	1	1	1	1	0.281	1	1	0.616	0.555	1	1	0	1
C	1	0	0.618	0.608	0	0	1	0.473	0.287	0	0	0.038	0.254	0.700	0.261
D	0.467	0.300	0.300	0.300	0.808	0.758	0.084	0.503	0.213	0.453	1	0.022	0.485	0.560	0.799
E	0.700	0.300	0.733	0.726	0.300	0.300	0.784	0.902	0.653	0.141	0.778	0	0	0.740	0.839
Remark	A: Shallow ground source heat pump, B: Solar collectors, C: Household biomass boilers, D: Solar-ground source heat pump hybrid system, E: Solar-household biomass boilers hybrid system														

4.3 Weight calculation

4.3.1 Subjective weights based on the improved FAHP method

The fuzzy pairwise comparison matrix is created by experts as shown in Table 7.

Table 7 Fuzzy complementary comparison matrix regarding the main criteria.

	Economic	Environmental	Energy	Social-political	Technical
Economic	0.5	0.6	0.7	0.8	0.9
Environmental	0.4	0.5	0.6	0.7	0.8
Energy	0.3	0.4	0.5	0.5	0.7
Social-political	0.2	0.2	0.5	0.5	0.7
Technical	0.1	0.2	0.3	0.3	0.5

The fuzzy consistency comparison matrix is generated according to the flow chart (Fig. 3).

Table 8 Fuzzy consistency comparison matrix regarding the main criteria.

	Economic	Environmental	Energy	Social-political	Technical	Weight
Economic	0.5	0.55	0.61	0.64	0.71	0.251
Environmental	0.45	0.5	0.56	0.59	0.66	0.226
Energy	0.39	0.44	0.5	0.47	0.6	0.19
Social-political	0.36	0.41	0.53	0.5	0.57	0.187
Technical	0.29	0.34	0.4	0.43	0.5	0.146

As illustrated in Table 8, economic performance has the highest weight of 0.251, followed by environmental (0.226), energy (0.19), social-political (0.187) and technical performance (0.146). It indicates that the economy profoundly impedes rural RE development in the experts' opinion. The detailed pairwise comparisons matrices of sub-criteria are provided in Appendix. Regarding the economic dimension, operation cost (C11) is slightly preferred to investment cost (C12). SO_2 emissions (C21) are ranked as the priority sub-criteria from an environmental perspective due to its toxicity, followed by NO_x, dust and CO_2 emissions. RE potentials (C31) have surfaced as the most important sub-criteria in an energy aspect as compared to energy accessibility and renewability. From the social-political aspect, policy subsidy incentives (C41) ranks first as governments play a crucial role in RE technology promotion. The current utilization rate (C43) reflects policy incentives (C41) and user preferences (C42) to a certain extent. Technical maturity (C51) is the highest-ranked aspect within the technical criteria. It embodies operability and market penetration. Operational reliability (C52) is found to be moderately important and system flexibility (C53) the least important.

4.3.2 Objective weights based on the CRITIC method

As set out in Section 2.3.2, objective weights are calculated based on the contrast intensity and conflicts between evaluation indicators (Table 9).

Table 9 CRITIC results for each criterion.

	Criterion	σ_j	C_j	ω_j
Economic	C_{11}	0.370	7.585	0.102
	C_{12}	0.409	3.679	0.049
Environmental	C_{21}	0.388	4.127	0.055
	C_{22}	0.387	4.094	0.055
	C_{23}	0.407	4.555	0.061
	C_{24}	0.394	4.269	0.057
Energy	C_{31}	0.441	7.139	0.096
	C_{32}	0.398	4.075	0.055
	C_{33}	0.396	3.772	0.051
Social-political	C_{41}	0.396	5.560	0.075
	C_{42}	0.373	4.997	0.067
	C_{43}	0.427	4.184	0.056
Technical	C_{51}	0.394	4.738	0.064
	C_{52}	0.371	7.456	0.100
	C_{53}	0.427	4.310	0.058

4.3.3 Integrated weights based on genetic algorithm

It is scientific and reasonable to combine the benefits of subjective and objective weights. Genetic algorithm is employed to reduce the randomness of subjective evaluation and the sidedness of objective information. It is suitable for optimization problems with small search spaces. Genetic algorithm considers various search points in the search space simultaneously, so it can provide rapid convergence with globally optimal solutions. It makes the combined weights a more accurate representation of the information on subjective and objective weights. The fitness function can be given as follows (Anagnostopoulos and Mamanis, 2011):

$$min f(a) = \sum_{i=1}^{p} \sum_{j=1}^{n} (\widetilde{\omega}_{ij} - \widehat{\omega}_j)^2 \quad (17)$$

$$s.t. \sum_{j=1}^{n} \widehat{\omega}_j = 1 \quad (18)$$

where $\widetilde{\omega}_{ij}$ is the weight of the *j*th criterion for the *i*th method, $\widehat{\omega}_j$ represents the combination weight of the *j*th criterion, *p* is the number of evaluation methods, and *n* represents the number of criteria.

Integrated weights $\widehat{\omega}_j$ are obtained as presented in Table 10.

Table 10 Integrated weights of evaluation criteria.

	Criterion	$\widehat{\omega}_j$
Economic	C_{11}	0.108
	C_{12}	0.093
Environmental	C_{21}	0.060
	C_{22}	0.058
	C_{23}	0.058
	C_{24}	0.052
Energy	C_{31}	0.090
	C_{32}	0.057
	C_{33}	0.049

Social-political	C_{41}	0.075
	C_{42}	0.065
	C_{43}	0.053
Technical	C_{51}	0.061
	C_{52}	0.074
	C_{53}	0.049

The subjective weights, objective weights and integrated weights of the evaluation criteria are summarized in Fig.6.

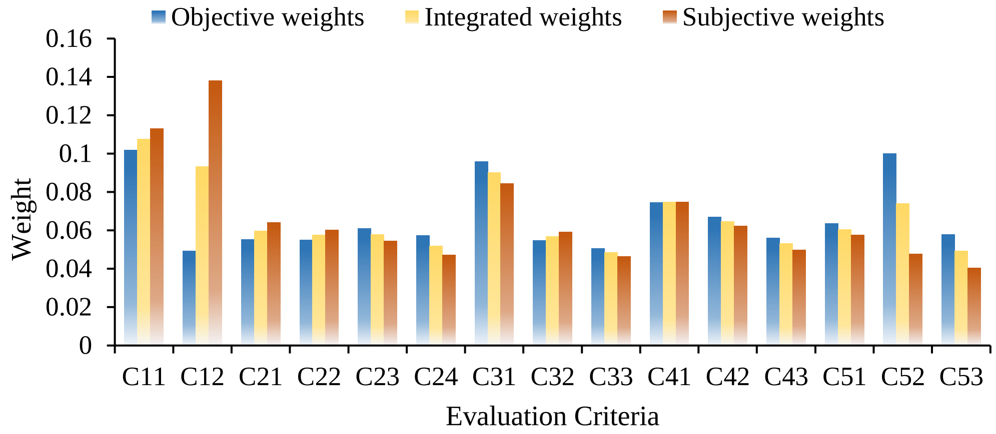


Fig. 6. Change curve of the criteria weights.

Compared with the subjective weight ranking, the combined weights varied minimally except for C12 (operation cost) and C52 (operational reliability). C12 is strongly correlated with the other indicators and C52 is weakly correlated, resulting in low and high objective weights respectively. C11, C12 and C31 are the criteria with larger integrated weights, corresponding to investment cost, operation cost and RE potentials, respectively. C33 and C53 are the criteria with smaller weights, corresponding to energy renewability and system flexibility.

4.4 **SPA-cloud model based approach**

4.4.1 Analysis by SPA evaluation

Once the weights have been obtained, the SPA method can be implemented to determine the priority of the five systems.

The connection degree μ_{11} for investment cost (C11) of system A can be calculated by Eq. (19) :

$$\mu_{11} = 0 + 0i_1 + 0.167i_2 + 0.833i_3 + 0j \tag{19}$$

After the same does to the other criteria, the connectivity connection degree μ_1 of system A can be expressed as Eq. (20) :

$$\mu_1 = \sum_{p=1}^{15} \omega_p \mu_{p1} = 0.191 + 0i_1 + 0.041i_2 + 0.262i_3 + 0.505j \tag{20}$$

The final score for system A is:

$$0.191 \times 1 + 0 \times 0.5 + 0.041 \times 0 + 0.262 \times (-0.5) + 0.505 \times (-1) = -0.183$$

The other four RE systems are calculated in the same steps above, as illustrated in Table 11.

Table 11 Connected degree, score, evaluation level and ranking of the alternatives.

System	Connected degree (μ)	Score	Level	Ranking
A	$0.191+0.262i_1+0.041i_2+0i_3+0.505j$	-0.183	III	4
B	$0.587+0.062\, i_1+0.079i_2+0.074i_3+0.197j$	0.384	II	1
C	$0.201+0.111i_1+0.128i_2+0.114i_3+0.445j$	-0.246	IV	5
D	$0.204+0.024i_1+0.316i_2+0.268i_3+0.188j$	-0.106	III	3
E	$0.27+0.322i_1+0.02i_2+0.196i_3+0.192j$	0.142	III	2
Remark	A: Shallow ground source heat pump, B: Solar collectors, C: Household biomass boilers, D: Solar-ground source heat pump hybrid system, E: Solar-household biomass boilers hybrid system			

Results indicate that the feasibility of the five RE systems in Pingtou Town can be placed in order as B＞E＞D＞A＞C.

4.4.2 Sensitivity analysis

Sensitivity analysis is performed to derive useful insights on the robustness of the obtained results. Minor variations in weights may lead to significant variations in findings. Therefore, it is necessary to test whether the results would qualitatively change if the weights fluctuated. As present in Table 12, four cases are taken in the analysis: equal weights (Case I), weighting fluctuates 10% (Case II), 20% (Case III) and 30% (Case IV).

Table 12 Weights of criteria with different cases.

	Basic case	Case I	Case II	Case III	Case IV
C_{11}	0.108	0.067	0.097	0.086	0.075
C_{12}	0.093	0.067	0.084	0.075	0.065
C_{21}	0.060	0.067	0.054	0.048	0.042
C_{22}	0.058	0.067	0.052	0.046	0.040
C_{23}	0.058	0.067	0.052	0.046	0.040
C_{24}	0.052	0.067	0.047	0.042	0.036
C_{31}	0.090	0.067	0.081	0.072	0.063
C_{32}	0.057	0.067	0.063	0.068	0.074
C_{33}	0.049	0.067	0.053	0.058	0.063
C_{41}	0.075	0.067	0.082	0.090	0.097
C_{42}	0.065	0.067	0.071	0.078	0.084
C_{43}	0.053	0.067	0.058	0.064	0.069
C_{51}	0.061	0.067	0.067	0.073	0.079
C_{52}	0.074	0.067	0.081	0.089	0.096
C_{53}	0.049	0.067	0.058	0.066	0.075

The SPA method is conducted based on the weights of the different cases. The results are illustrated in Fig. 7.

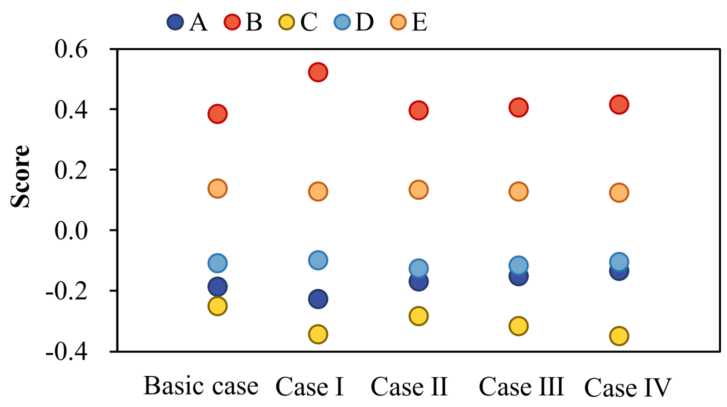


Fig. 7. Results of the sensitivity analysis.

It can be seen in Fig. 7 that the ranking order of the five RE systems remains the same in all five cases, namely B>E>D>A>C. Therefore, it is identified that the proposed framework and analysis results are reasonable and robust.

4.4.3 Cloud model-based fuzziness visualization

The numerical parameters of the evaluation levels generated by the forward cloud model and the parameters of the alternatives generated by the reverse cloud model are shown in Table 13 and Table 14, respectively.

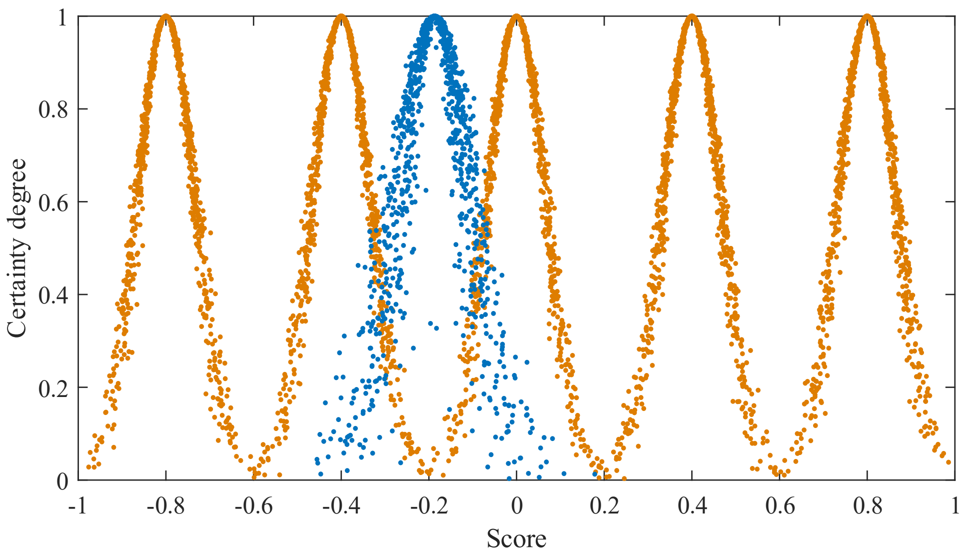
Table 13 Numerical parameters of the evaluation levels.

	[0, 0.2)	[0.2, 0.4)	[0.4, 0.6)	[0.6, 0.8)	[0.8, 1]
Ex	-0.8	-0.4	0	0.4	0.8
En	0.0667	0.0667	0.0667	0.0667	0.0667
He	0.0067	0.0067	0.0067	0.0067	0.0067

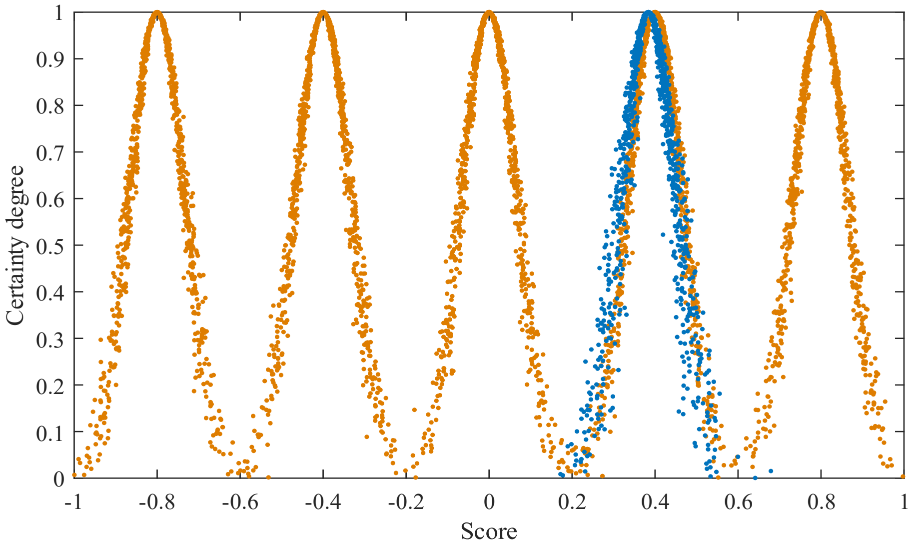
Table 14 Numerical parameters of the alternatives.

	System A	System B	System C	System D	System E
Ex	-0.187	0.384	-0.251	-0.110	0.137
En	0.085	0.066	0.140	0.088	0.083
He	0.021	0.012	0.059	0.063	0.065

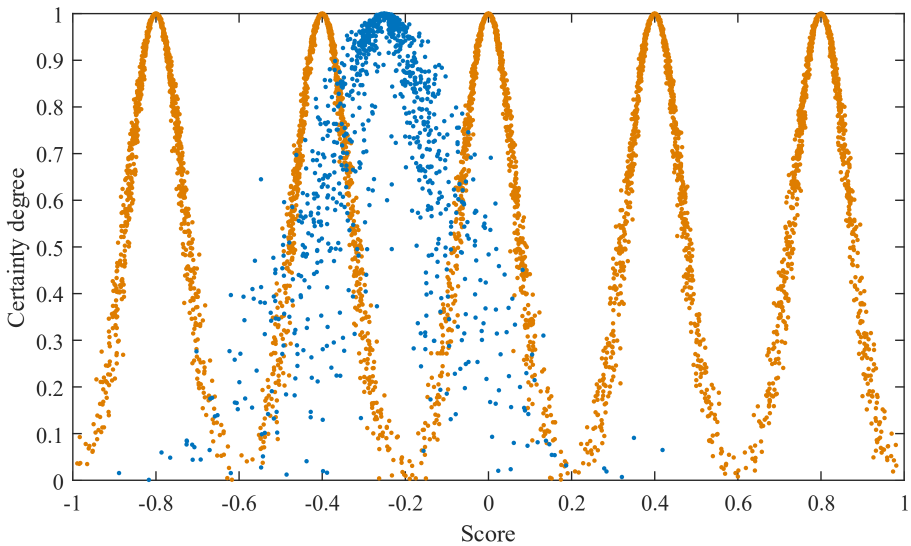
The clouds of the five RE systems are presented in Fig. 8.



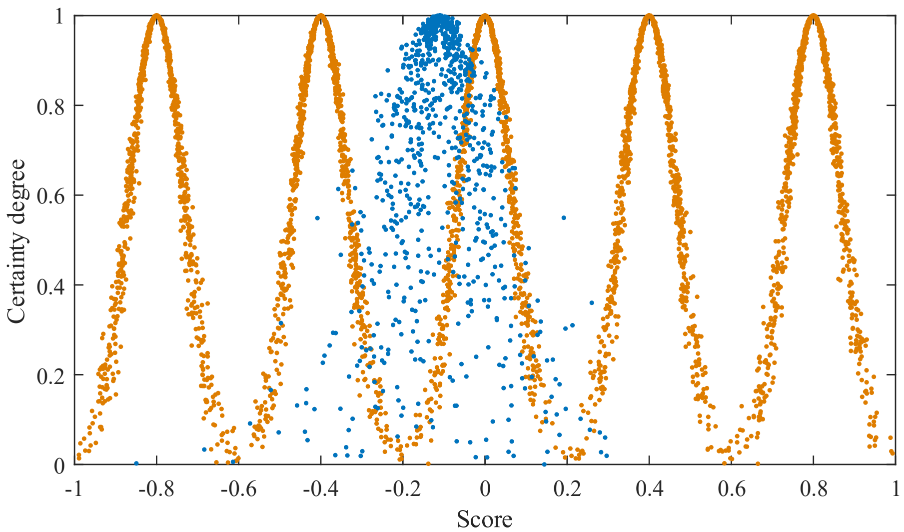
(a) Shallow ground source heat pump



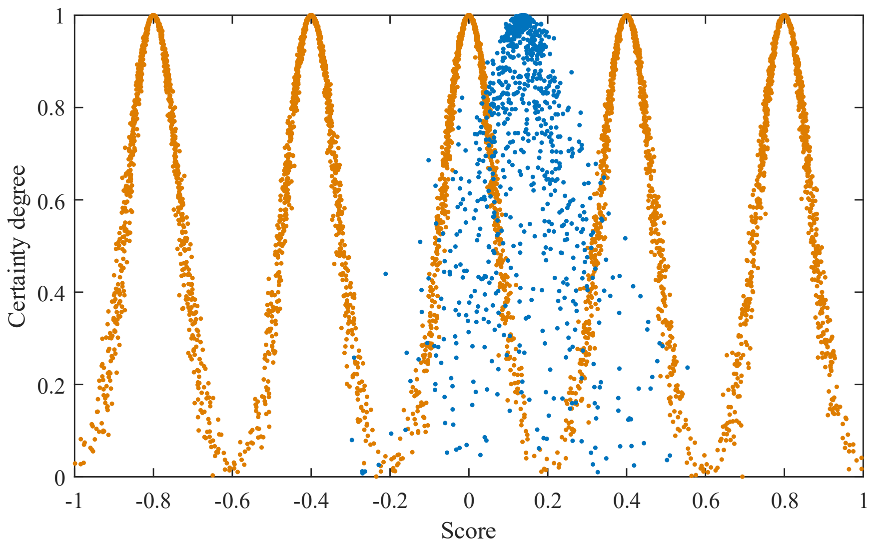
(b) Solar collectors



(c) Household biomass boilers



(d) Solar-ground source heat pump hybrid system



(e) Solar-household biomass boilers hybrid system

Fig. 8. The clouds of the five RE systems. Note: the blue represents the alternatives, and the yellow represents the evaluation level.

The clouds demonstrate not only the level of alternatives (*Ex*), but also the evaluation ambiguity (*En*) and the dispersion of alternative performance under each evaluation criterion (*He*).

The level of the alternatives can be determined by the proximity of the alternative clouds to the evaluation level clouds. The indicator performance of systems A and B are concentrated, while performances for systems C, D and E are more dispersed. System B outperforms the other four alternatives due to the highest score and the least judgmental ambiguity.

5 Discussion

5.1 Result verification

The evaluation framework is typically simplified to 3 basic criteria groups of economic, energy and environmental performance (Cavallaro and Ciraolo, 2005; Ju et al., 2016). This study introduces subjectivity while expanding the evaluation criteria. In this section, a more intuitive assessment framework and typical evaluation methods are employed to verify the rationality of the results. The evaluation framework consisting of economic, energy, and environmental performance is completely objective. It includes seven sub-criteria (Fig. 9).

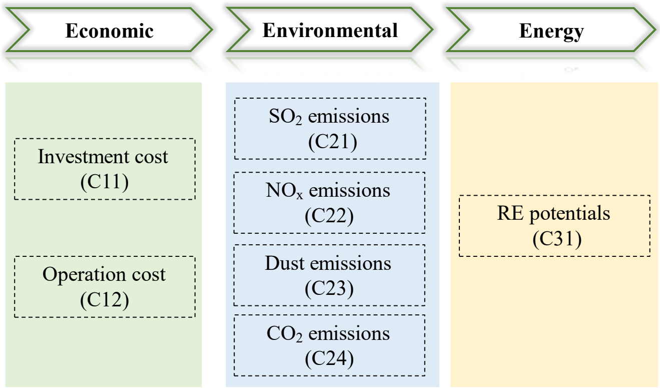


Fig. 9. Simplified evaluation framework.

5.1.1 AHP-CRITIC approach

Subjective and objective weights are often integrated to determine the importance of indicators(Qi et al., 2022; Tabak et al., 2019). Then the linear weighting function can be used to derive the total combined performance (Yu, S. et al., 2019). The integrated weights are calculated according to the FAHP-CRITIC method described in sections 2.3.1 and 2.3.2. The subjective weights, objective weights, and integrated weights are summarized as follows.

Table 15 The subjective weights, objective weights, and integrated weights of the indicators.

Criterion	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}
Subjective weights	0.292	0.357	0.065	0.061	0.055	0.048	0.122
Objective weights	0.170	0.090	0.083	0.083	0.130	0.121	0.323
Integrated weights	0.245	0.198	0.081	0.079	0.094	0.084	0.219

Based on the normalized decision matrix (Table 6), the comprehensive score of each system can be determined by Eq. (21).

$$S_i = \sum_{j=1}^{n} x'_{ij} \cdot \widehat{\omega}_{ij} \tag{21}$$

where S_i is the comprehensive score of each system, $\widehat{\omega}_{ij}$ is the weight of the jth indicator with respect to the ith system, and x'_{ij} is the normalized value.

The comprehensive scores, rankings by the AHP-CRITIC method and the original rankings are presented in Table 16.

Table 16 The comprehensive score, ranking by the AHP-CRITIC method and the original ranking of each system.

System	Score	Ranking	Original ranking
Shallow ground source heat pump	0.29	5	4
Solar collectors	0.60	1	1
Household biomass boilers	0.56	3	5
Solar-ground source heat pump hybrid system	0.38	4	3
Solar-household biomass boilers hybrid system	0.57	2	2

5.1.2 TOPSIS approach

As depicted in Table 1, TOPSIS allocates the scores to each alternative based on their geometric distance from positive and negative ideal solutions (Zaidan et al., 2015). It is extensively employed in the ranking of multi-objective decisions (Choudhary and Shankar, 2012; Joshi et al., 2011).

The general TOPSIS process has the following steps:

Step 1: Construct the normalized decision matrix. The decision matrix (Table 5) can be normalized to the matrix $R = (r_{ij})_{m\times n}$ using the normalization method:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \tag{22}$$

where $i = 1, \dots m$, and $j = 1, \dots n$.

Step 2: Determine the positive ideal solution A^+ and the negative ideal solution A^-.

They can be calculated as follows.

$$A^{+} = \{r_1^{+}, r_2^{+}, r_3^{+}, \cdots, r_m^{+}\} max_i r_{ij} = \{(max_i r_{ij} | j \epsilon J), (min_i r_{ij} | j \epsilon J^{-})\} \quad (23)$$

$$A^{-} = \{r_1^{-}, r_2^{-}, r_3^{-}, \cdots, r_m^{-}\} max_i r_{ij} = \{(max_i r_{ij} | j \epsilon J), (min_i r_{ij} | j \epsilon J^{-})\} \quad (24)$$

where J is associated with the positive factors and J' is associated with the negative factors.

Step 3: Calculate the distance of alternatives to the positive ideal solution (D_i^{+}) and the negative ideal (D_i^{-}) solution as follows.

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} (r_{ij} - r_j^{+})^2},\ i = 1, \ldots, m. \quad (25)$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} (r_{ij} - r_j^{-})^2},\ i = 1, \ldots, m. \quad (26)$$

Step 4: Calculate the relative closeness coefficient c_i to the ideal solution by Eq. (27).

$$c_i = \frac{D_i^{-}}{D_i^{-} + D_i^{+}} \quad (27)$$

The set of the alternative can be ranked according to c_i, the highest value the better performance.

D_i^{+}, D_i^{-}, c_i, and rankings calculated based on the above steps are shown in Table 17.

Table 17 D_i^{+}, D_i^{-}, c_i, and rankings of each system.

System	D_i^{+}	D_i^{-}	c_i	Ranking	Original ranking
Shallow ground source heat pump	0.630	0.299	0.322	5	4
Solar collectors	0.425	0.583	0.578	1	1
Household biomass boilers	0.511	0.522	0.505	3	5
Solar-ground source heat pump hybrid system	0.515	0.313	0.378	4	3
Solar-household biomass boilers hybrid system	0.380	0.447	0.541	2	2

5.1.3 Comparative analysis

As illustrated in Tables 15 and 16, the two validation methods yielded the same rankings, both of which differed slightly from the original rankings. The reason is that the new evaluation framework eliminates criteria that require subjective judgments (socio-political and technical performance). System C (household biomass boilers) performs poorly in social and technical aspects. It resulted in an improvement in its ranking from the original last place to the third place after simplifying the framework. Subsequently, the ranking of system A and system D have changed marginally due to the variation of system C. Indeed, despite the subjective nature of the excluded criteria, technical support and social effect are meaningful for the holistic evaluation. Therefore, the evaluation framework and method proposed in this study proved to be rational and valid. Although the methods of the existing studies were able to demonstrate similar valid results, they failed to visualize the uncertainty in the evaluation process (Ayağ and Samanlioglu, 2020; Zaidan et al., 2015). It further proves that the approach proposed in this study is reliable, comprehensive, and advanced.

5.2 Result analysis

According to Table 11, solar collectors perform the best, followed by solar-household biomass boilers hybrid system, solar-ground source heat pump hybrid system, shallow ground source heat pump, and household biomass boilers. The ranking of the five RE systems shows that solar energy is quite popular as the “low hanging fruit”, followed by geothermal energy and biomass. In Pingtou Town, solar energy is pollution-free and highly utilized, furthermore, the government is expected to increase subsidies to cover the expensive initial investment. Geothermal energy utilization is restricted by extraction policies and geological conditions. Moreover, rural households are scattered, so an appropriate heating radius needs to be considered in the application of ground source heat pumps for central heating in rural areas. Biomass is the most abundant resource of the three RESs in Pingtou Town, but the low level of biomass molding technology leads to the biomass boiler ranking last. In addition, better performance can be achieved in energy complementary systems. Solar collectors combined with biomass boilers and ground source heat pump systems ranked second and third, respectively.

5.3 Policy recommendations

Renewable energy for heating in China is still in its infancy. To further consolidate and deepen the development of RE heating, policy measures can be taken from the following aspects.

The development of RE is inseparable from government support. Currently, there is a subsidy policy for geothermal heating and photovoltaic power generation in Pingtou Town, but not for biomass. Firewood is mostly used for household biomass heating in the form of fireplaces and stoves. Efficient utilization methods such as biogas and biomass stoves should be promoted. The investment from private sectors in RE technologies need to be facilitated. Local RE manufacturing facilities are supposed to be developed. It will not only lower the cost but also generates employment opportunities. Underdeveloped areas like Pingtou Town are too conservative to achieve a notable share of RE. RE heating demonstration projects should be carried out as widespread application cases. In addition, investment in resource exploration should be stepped up to provide basic information for RE applications.

Improved RE support schemes, coupled with improvements in technology costs, will drive up the progress in RE production and contribute to the development of a low carbon economy.

6 Conclusions

In this paper, a novel evaluation model is proposed based on the FAHP, CRITIC, SPA method and cloud model. Then the model is employed in the selection of RE systems considering five dimensions and 15 evaluation indicators. The proposed evaluation framework develops a novel method to associate SPA with cloud models to visualize the ambiguity in evaluation process. It is applied to prioritize five RE heating systems in Pingtou Town, Shaanxi Province, China. This study intends to demonstrate a new approach to select RE and provide support for multi-attribute decision problems. The main conclusions can be drawn as follows:

(1) A framework for the evaluation of RE heating systems is presented. The framework integrates economic, environmental, energy, social and technological performance, and gets information from questionnaires, existing literature, calculations and expert evaluations. It is comprehensive and can be applied to different RE evaluation projects.

(2) The combined weights of the evaluation criteria are determined. The expert experience and data information are both taken into account. The subjective weights are obtained by the improved AHP method, and the objective weights are calculated by the CRITIC method. The largest weights are given to investment cost and operating cost, at 0.108 and 0.093, respectively. The smallest weights are given to energy renewability and system flexibility, both at 0.049.

(3) The ranking of the five RE systems is obtained by the SPA method. Solar collectors outperform other alternatives scoring 0.384, followed by solar-household biomass boilers hybrid systems (0.137), solar-ground source heat pump hybrid systems (-0.11) and shallow ground source heat pump (-0.187). Biomass boilers are ranked last with a score of -0.251.

(4) The fuzziness of the SPA method and the dispersion of each indicator performance are visualized by the cloud model. Solar collectors and shallow ground source heat pumps are evaluated with less fuzziness, while solar-household biomass boilers hybrid systems, solar-ground source heat pump hybrid systems and biomass boilers are evaluated with more fuzziness.

The framework facilitates decision makers to better understand ambiguity in decision making, thus improving the accuracy of the decision. The insights from the present method also provide implications for other locations as well. The proposed evaluation framework can be modified to address other decision problems such as technology selection, supplier selection, facility location as well as other sectors.

7 Limitations and future recommendations

There are some limitations to be tackled in future studies. It is possible for an expert not to have sufficient time, motivation or knowledge on a certain topic, which can prevent the expert from perfectly stating the degree of preference among the available alternatives. As well, RESs cannot be accurately estimated due to policy constraints. These kinds of constraints may slightly affect the evaluation results.

In future work, rational consistency can be more widely validated in typical fuzzy multi-objective evaluations of industry, energy investment, etc. Furthermore, the carbon emissions, energy efficiency indicators are also potential research points, which can be incorporated in the evaluation framework. Moreover, the performance of evaluation indicators should be more accurate and as little subjective as possible. For example, roof areas in the solar resource calculation can be identified by pattern recognition algorithms.

Acknowledgments

The authors are grateful for the financial support provided by the China National Key R&D Program [Grant No. 2020YFD1100305-02].

Appendix

Table 1 Fuzzy consistency comparison matrix regarding the economic criteria.

	Operation cost	Investment cost	Weight
Operation cost	0.5	0.525	0.45
Investment cost	0.475	0.5	0.55

Table 2 Fuzzy consistency comparison matrix regarding the environmental criteria.

	SO_2	NO_x	Dust	CO_2	Weight
SO_2	0.5	0.525	0.5625	0.6125	0.283

NO_x	0.475	0.5	0.5375	0.5875	0.267
Dust	0.4375	0.4625	0.5	0.55	0.242
CO_2	0.3875	0.4125	0.45	0.5	0.208

Table 3 Fuzzy consistency comparison matrix regarding the energy criteria.

	RE potentials	Energy accessibility	Energy renewability	Weight
RE potentials	0.5	0.6	0.65	0.444
Energy accessibility	0.4	0.5	0.55	0.311
Energy renewability	0.35	0.45	0.5	0.244

Table 4 Fuzzy consistency comparison matrix regarding the social-political criteria.

	Policy subsidy incentives	User preferences	Current utilization	Weight
Policy subsidy incentives	0.5	0.6	0.7	0.4
User preferences	0.4	0.5	0.6	0.333
Current utilization	0.3	0.4	0.5	0.267

Table 5 Fuzzy consistency comparison matrix regarding the technical criteria.

	Policy subsidy incentives	User preferences	System flexibility	Weight
Technical maturity	0.5	0.6	0.8	0.394
Operational reliability	0.4	0.5	0.6	0.328
System flexibility	0.3	0.4	0.5	0.278

Reference

Adams, S., Acheampong, A.O., 2019. Reducing carbon emissions: the role of renewable energy and democracy. Journal of Cleaner Production 240, 118245.

Administration, N.E., 2017. Views on the promotion of renewable energy for heating.

Aili, Z.K.-q.X., 1996. Set pair theory-a new theory method of non-define and its applications. Syst. Eng 1(3). [In Chinese]

Aloini, D., Dulmin, R., Mininno, V., Raugi, M., Schito, E., Testi, D., Tucci, M., Zerbino, P., 2021. A multi-objective methodology for evaluating the investment in building-integrated hybrid renewable energy systems. Journal of Cleaner Production 329.

Amer, M., Daim, T.U., 2011. Selection of renewable energy technologies for a developing county: A case of Pakistan. Energy for Sustainable Development 15(4), 420-435.

Anagnostopoulos, K.P., Mamanis, G., 2011. The mean–variance cardinality constrained portfolio optimization problem: An experimental evaluation of five multiobjective evolutionary algorithms. Expert Syst. Appl.Expert Systems with Applications 38 (11), 14208–14217.

Asante, D., Ampah, J.D., Afrane, S., Adjei-Darko, P., Asante, B., Fosu, E., Dankwah, D.A., Amoh, P.O., 2022. Prioritizing strategies to eliminate barriers to renewable energy adoption and development in Ghana: A CRITIC-fuzzy TOPSIS approach. Renewable Energy 195, 47-65.

Atmaca, E., Basar, H.B., 2012. Evaluation of power plants in Turkey using Analytic Network Process (ANP). Energy 44(1), 555-563.

Ayağ, Z., Samanlioglu, F., 2020. Fuzzy AHP-GRA approach to evaluating energy sources: a case of Turkey. International Journal of Energy Sector Management 14(1), 40-58.

Babatunde, M.O., Ighravwe, D.E., 2019. A CRITIC-TOPSIS framework for hybrid renewable energy systems evaluation under techno-economic requirements. Journal of Project Management, 109-126.

Büyüközkan, G., Güleryüz, S., 2016. An integrated DEMATEL-ANP approach for renewable energy resources selection in Turkey. International Journal of Production Economics 182, 435-448.

Cansino, J.M., Pablo-Romero, M.d.P., Román, R., Yñiguez, R., 2011. Promoting renewable energy sources for heating and cooling in EU-27 countries. Energy Policy 39(6), 3803-3812.

Cavallaro, F., Ciraolo, L., 2005. A multicriteria approach to evaluate wind energy plants on an Italian island. Energy policy 33(2), 235-244.

Çelikbilek, Y., Tüysüz, F., 2016. An integrated grey based multi-criteria decision making approach for the evaluation of renewable energy sources. Energy 115, 1246-1258.

Choudhary, D., Shankar, R., 2012. An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India. Energy 42(1), 510-521.

Davoudabadi, R., Mousavi, S.M., Mohagheghi, V., 2021. A new decision model based on DEA and simulation to evaluate renewable energy projects under interval-valued intuitionistic fuzzy uncertainty. Renewable Energy 164, 1588-1601.

Deyi, L., Haijun, M., Xuemei, S., 1995. Membership clouds and membership cloud generators. Journal of computer research and development 32(6), 15-20.

Diakoulaki, D., Mavrotas, G., Papayannakis, L., 1995. Determining objective weights in multiple criteria problems: The critic method. Computers & Operations Research 22(7), 763-770.

Dogan, E., Seker, F., 2016. The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. Renewable and Sustainable Energy Reviews 60, 1074-1085.

Dong, F., Shi, L., 2019. Regional differences study of renewable energy performance: A case of wind power in China. Journal of Cleaner Production 233, 490-500.

Erdin, C., Ozkaya, G., 2019. Turkey's 2023 Energy Strategies and Investment Opportunities for Renewable Energy Sources: Site Selection Based on ELECTRE. Sustainability 11(7).

Garg, H., Kumar, K., 2019. A novel possibility measure to interval-valued intuitionistic fuzzy set using connection number of set pair analysis and its applications. Neural Computing and Applications 32(8), 3337-3348.

Gong, X., Yang, M., Du, P., 2021. Renewable energy accommodation potential evaluation of distribution network: A hybrid decision-making framework under interval type-2 fuzzy environment. Journal of Cleaner Production 286.

Guo, Y., Meng, X., Wang, D., Meng, T., Liu, S., He, R., 2016. Comprehensive risk evaluation of long-distance oil and gas transportation pipelines using a fuzzy Petri net model. Journal of Natural Gas Science and Engineering 33, 18-29.

Han, H., Wu, S., 2018. Rural residential energy transition and energy consumption intensity in China. Energy Economics 74, 523-534.

Henninger, S., Jaeger, J., Hofmann, T., 2017. Analytical assessment of renewable energy sources and energy storage concerning their merits for the electric power system. Energy Procedia 135, 398-409.

Joshi, R., Banwet, D.K., Shankar, R., 2011. A Delphi-AHP-TOPSIS based benchmarking framework for performance improvement of a cold chain. Expert Systems with Applications 38(8), 10170-10182.

Ju, L., Tan, Z., Li, H., Tan, Q., Yu, X., Song, X., 2016. Multi-objective operation optimization and evaluation model for CCHP and renewable energy based hybrid energy system driven by distributed energy resources in China. Energy 111, 322-340.

Karakas, E., Yildiran, O.V., 2019. Evaluation of Renewable Energy Alternatives for Turkey via Modified Fuzzy AHP. International Journal of Energy Economics and Policy 9(2), 31-39.

Khan, M.J., Kumam, P., Alreshidi, N.A., Shaheen, N., Kumam, W., Shah, Z., Thounthong, P., 2020. The Renewable Energy Source Selection by Remoteness Index-Based VIKOR Method for Generalized Intuitionistic Fuzzy Soft Sets. Symmetry 12(6).

Korsavi, S.S., Zomorodian, Z.S., Tahsildoost, M., 2018. Energy and economic performance of rooftop PV panels in the hot and dry climate of Iran. Journal of Cleaner Production 174, 1204-1214.
Kumar, K., Chen, S.-M., 2021. Multiattribute decision making based on interval-valued intuitionistic fuzzy values, score function of connection numbers, and the set pair analysis theory. Information Sciences 551, 100-112.
Lehr, U., Lutz, C., Edler, D., 2012. Green jobs? Economic impacts of renewable energy in Germany. Energy Policy 47, 358-364.
Li, T., Li, A., Guo, X., 2020. The sustainable development-oriented development and utilization of renewable energy industry——A comprehensive analysis of MCDM methods. Energy 212.
Lin, B., Jia, Z., 2020. Is emission trading scheme an opportunity for renewable energy in China? A perspective of ETS revenue redistributions. Applied Energy 263, 114605.
Liu, H.-C., Wang, L.-E., Li, Z., Hu, Y.-P., 2019. Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method. IEEE Transactions on Fuzzy Systems 27(1), 84-95.
Mastrocinque, E., Ramírez, F.J., Honrubia-Escribano, A., Pham, D.T., 2020. An AHP-based multi-criteria model for sustainable supply chain development in the renewable energy sector. Expert Systems with Applications 150.
Matsumoto, K.i., Morita, K., Mavrakis, D., Konidari, P., 2017. Evaluating Japanese policy instruments for the promotion of renewable energy sources. International Journal of Green Energy 14(8), 724-736.
Office, C.D.G., 2021. Pingtou Town. http://www.chencang.gov.cn/art/2021/4/14/art_8167_1173624.html. [In Chinese]
Pérez de Arce, M., Sauma, E., Contreras, J., 2016. Renewable energy policy performance in reducing CO2 emissions. Energy Economics 54, 272-280.
Qi, J., Zhang, Y., Zhang, J., Chen, Y., Wu, C., Duan, C., Cheng, Z., Pan, Z., 2022. Research on the Evaluation of Geological Environment Carrying Capacity Based on the AHP-CRITIC Empowerment Method. Land 11(8), 1196.
Rani, P., Mishra, A.R., Pardasani, K.R., Mardani, A., Liao, H., Streimikiene, D., 2019. A novel VIKOR approach based on entropy and divergence measures of Pythagorean fuzzy sets to evaluate renewable energy technologies in India. Journal of Cleaner Production 238.
Raugei, M., Leccisi, E., 2016. A comprehensive assessment of the energy performance of the full range of electricity generation technologies deployed in the United Kingdom. Energy Policy 90, 46-59.
Saaty, T.L., 1980. The analytic hierarchy process, new york: Mcgrew hill. International, Translated to Russian, Portuguesses and Chinese, Revised edition, Paperback (1996, 2000), Pittsburgh: RWS Publications 9, 19-22.
Saidur, R., Abdelaziz, E.A., emirbas, A.D., Hossain, M.S., Mekhilef, S., 2011. A review on biomass as a fuel for boilers. Renewable and Sustainable Energy Reviews.
Şengül, Ü., Eren, M., Eslamian Shiraz, S., Gezder, V., Şengül, A.B., 2015. Fuzzy

TOPSIS method for ranking renewable energy supply systems in Turkey. Renewable Energy 75, 617-625.
Su, F., Li, P., He, X., Elumalai, V., 2020. Set pair analysis in earth and environmental sciences: development, challenges, and future prospects. Exposure and Health 12(3), 343-354.
Tabak, Ç., Yıldız, K., Yerlikaya, M., 2019. Logistic location selection with Critic-Ahp and Vikor integrated approach. Data Science and Applications 2(1).
Wang, M., Liu, Y., Wang, D., Zhou, Y., Liu, J., 2018. Suitability analysis of auxilliary heat sources for solar heating in rural areas of Northwest China. Journal of HV&AC 48(4), 22-41. [In Chinese]
Wang, X.-q., Guo, Q., 2010. The priority of fuzzy complementary judgment matrix and its application in procurement tenders for government project, 2010 IEEE 17Th International Conference on Industrial Engineering and Engineering Management. IEEE, pp. 148-151.
Wang, Y., Jing, H., Yu, L., Su, H., Luo, N., 2016. Set pair analysis for risk assessment of water inrush in karst tunnels. Bulletin of Engineering Geology and the Environment 76(3), 1199-1207.
Wu, H.-W., Zhen, J., Zhang, J., 2020. Urban rail transit operation safety evaluation based on an improved CRITIC method and cloud model. Journal of Rail Transport Planning & Management 16.
Yao, J., Wang, G., Xue, B., Wang, P., Hao, F., Xie, G., Peng, Y., 2019. Assessment of lake eutrophication using a novel multidimensional similarity cloud model. J Environ Manage 248, 109259.
Yu, S., Zheng, Y., Li, L., 2019. A comprehensive evaluation of the development and utilization of China's regional renewable energy. Energy Policy 127, 73-86.
Yu, Y., Cheng, J., You, S., Ye, T., Zhang, H., Fan, M., Wei, S., Liu, S., 2019. Effect of implementing building energy efficiency labeling in China: A case study in Shanghai. Energy Policy 133, 110898.
Zaidan, A.A., Zaidan, B.B., Al-Haiqi, A., Kiah, M.L., Hussain, M., Abdulnabi, M., 2015. Evaluation and selection of open-source EMR software packages based on integrated AHP and TOPSIS. J Biomed Inform 53, 390-404.
Zhang, L., Xin, H., Yong, H., Kan, Z., 2019. Renewable energy project performance evaluation using a hybrid multi-criteria decision-making approach: Case study in Fujian, China. Journal of Cleaner Production 206, 1123-1137.
Zhao, H., Li, N., 2015. Risk Evaluation of a UHV Power Transmission Construction Project Based on a Cloud Model and FCE Method for Sustainability. Sustainability 7(3), 2885-2914.
Zhao, K., 1989. Theory and analysis of set pair ea new concept and system analysis method, Conference thesis of system theory and regional planning. pp. 87-91.
Zheng, X., Yang, X., Miao, H., Liu, H., Yu, Y., Wang, Y., Zhang, H., You, S., 2022. A factor analysis and self-organizing map based evaluation approach for the renewable energy heating potentials at county level: A case study in China. Renewable and

Sustainable Energy Reviews 165, 112597.