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Research Article

Investment Efficiency Assessment of Distribution Network for the High Proportion of Renewable Energy: A Hybrid Multiattribute Decision-Making Method

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To cope with the high proportion of renewable energy connected to the grid under the carbon peak and neutrality goal, the investment in distribution network construction will account for more than 50% of the power grid companies' investment direction in distribution networks in China. According to the characteristics of distribution network investment under the high proportion of renewable energy, a new evaluation index system of distribution network investment efficiency is constructed from the three dimensions of power supply guarantee capacity, total carrying capacity and value creation capacity. Besides, it put forward the game theory combined weighting method based on fuzzy BWM (F-BWM) method and anti-entropy weight method (a-EWM) and the multi-attribute decision-making method of MARCOS based on Pearson coefficient instead of the covariance matrix and improved weighted Mahalanobis distance (I-M-MARCOS). Finally, eight typical distribution network projects in a province of China are selected for empirical analysis. The results show that the model has good applicability in the evaluation of distribution network investment efficiency, and expanding the scale of distribution network and flexibly adjusting resources are the key ways to improve the investment efficiency of distribution networks.

1. Introduction

With the transformation of China's economic development mode, the acceleration of urbanization, and the gradual deepening of power system reform, a novel power system with renewable energy as the main body is a vital prerequisite for leading the low-carbon development and transformation of the power system. Therefore, vigorously developing renewable energy and increasing the proportion of electric energy in terminal consumption are necessary guarantees to achieve the carbon peak and neutrality goal. When renewable energy is connected to the power system in large quantities, its impact on the grid will change as the penetration rate of renewable energy continues to increase. Therefore, when the penetration rate is greater than 50%, it can be considered that a high proportion of renewable energy access stage has been reached in the power grid, and the impact of renewable energy on the grid will change compared with the low proportion of renewable energy access stage [1, 2]. To cope with the high proportion of renewable energy connected to the power system, the distribution network will enter a new stage of development, and the investment in the distribution network needs to coordinate safety, quality, and efficiency benefits. Thus, the

investment efficiency of the distribution network with a high proportion of renewable energy connected to the grid has a new connotation. It is of great significance to evaluate it.

Regarding the evaluation index system of distribution network investment efficiency, some scholars have conducted in-depth research on the index system that characterizes the investment efficiency of distribution networks. For example, in [3], a two-layer index system for investment benefit evaluation is established, which considers unit investment efficiency and macro investment benefit. Reference [4] proposed a method of penetrating correlation analysis using direct mining data and constructed the core index of the investment efficiency of the distribution network, aiming at the characteristics of various types of distribution network equipment and related index data under the high-quality development of the distribution network.

In terms of the evaluation method of distribution network investment efficiency, some previous research on distribution network investment efficiency evaluation used econometric models to evaluate the economic efficiency of the distribution network [5]. However, econometric methods have high requirements for time series. The power industry is a complex system with countless uncertainties, which is unlikely to meet the basic needs of econometric models [6]. The DEA model is suitable for complex distribution network systems with multiple input and output indexes and can be better applied to evaluate power distribution network investment efficiency in various directions, such as distribution network operation, economic efficiency, and social and environmental efficiency [7–10]. However, the DEA method has higher requirements on data and mainly focuses on the relative efficiency of the evaluation object. The multiattribute decision-making method usually consists of two parts: index weighting and attribute integration. Among them, the practices of index weighting include subjective and objective weighting methods, such as the analytic hierarchy process, optimal and worst method, and entropy weight method. For attribute integration, commonly used methods include fuzzy comprehensive evaluation, matter-element extension method, and TOPSIS. The distribution network investment index has intense uncertainty and correlation, and the multiattribute decision-making method has good applicability. Thus, this paper intends to use the multiattribute decision-making method to evaluate the investment efficiency of the distribution network.

Under the background of rapid economic development, increasingly prominent environmental problems such as global warming, and the integration of a high proportion of renewable energy into the power grid, the investment efficiency of the distribution network has been given a broader meaning. Reference [11] proposed to include air pollution damage in investment assessment. Reference [12] studied the impact of grid infrastructure investment on the German macroeconomy after integrating renewable energy. Reference [13] assessed grid investment in Spain with a high share of renewable energy integration. Reference [14] selected distinct regions in the United States to study the relationship between photovoltaic energy storage and climate change, public health, and power supply security. Reference [15] builds a fuzzy optimal back-propagation neural network (BPNN) based on BPNN and fuzzy optimization strategy for cost-benefit analysis and measures the impact of some uncertain factors on the economy of investment projects. These studies show that the elements that characterize grid investment efficiency are changing with the integration of a high proportion of renewable energy into the grid. For example, the investment efficiency of projects such as electric vehicles and energy storage is closely related to the penetration rate of renewable energy in the grid [16, 17].

Under the background of the high proportion of grid-connected renewable energy, the development of distribution networks towards intelligence and informatization is an inevitable trend. Scholars have researched the investment of intelligent distribution networks in various directions. Reference [5] carried out the economic evaluation of power grid investment based on intelligent wise distribution network equipment. References [3, 18] studied the investment optimization of smart networks with different methods. Reference [19] sets the intelligence and digitization of the distribution network as the evaluation conditions to evaluate the innovative advantages of flexible resources. Reference [20] studies the contribution of self-assessment of power assets and smart grid components.

According to the above analysis, it can be found that the investment efficiency of the distribution network is comprehensive and systematic. Therefore, whether it is multi-attribute decision-making or input-output analysis, it is essential to build an index system that can fully reflect the investment efficiency of the distribution network. In the construction of a new power system, the distribution network needs to meet the power supply guarantee capacity, the comprehensive carrying capacity, and value creation capacity after a high proportion of renewable energy sources is connected. Thus, based on the existing research foundation, expanding the connotation of the investment efficiency of the distribution network plays an important role in enhancing the distribution network to cope with the high proportion of grid-connected renewable energy. In addition, the multiattribute decision-making method, as a relatively advanced evaluation method of power grid investment efficiency, has good applicability. However, considering the new connotation of distribution network investment efficiency in the context of the high proportion of grid-connected renewable energy, it is of great theoretical and practical significance to make targeted improvements to the existing methods of index weighting and attribute integration. Based on this, this paper proposes a new evaluation method to measure the investment efficiency of distribution networks based on the high proportion of renewable energy grid background. This paper plans to use the fuzzy BWM to calculate the subjective weight. The fuzzy BWM simplifies the number of pairwise comparisons between the indicators and reduces the risk of inconsistency of the indicators while considering the uncertainty of the indicators. It is suitable for evaluating the investment efficiency of the distribution network. For example, Reference [21] adopts a new fuzzy BWM for solving nonlinear problems in research; Reference [22] adopted a novel fuzzy decision-making technique,

namely, trapezoidal fuzzy Best-Worst method (fuzzy BWM), which is based on Best-Worst method (BWM) and Trapezoidal fuzzy number.

However, the commonly used multiattribute decision-making methods have some shortcomings: (1) The traditional BWM does not consider the uncertainty problem, and the index difference reflected by the entropy value in the entropy weight method is too sensitive, which may lead to the problem that the index weight is too small in the weight allocation. (2) For the traditional Mahalanobis distance, only the covariance between attribute indicators is considered, which may lead to unstable calculation results and easily ignore the differences between attributes.

The main contribution of this paper has three aspects:

(1) The evaluation index system for investment efficiency of high-proportion renewable energy distribution network is constructed from the three dimensions of power supply guarantee capacity, comprehensive carrying capacity, and value creation capacity.

(2) A game theory-combined weighting model based on fuzzy BWM-anti-entropy weight method is proposed to determine the weights. Using the Pearson correlation coefficient instead of weighted Mahalanobis distance of covariance, a hybrid comprehensive evaluation model based on weighted Mahalanobis distance and improved MARCOS method is proposed. Thus, the shortcomings of a single method are overcome.

(3) Eight typical regional distribution networks in a province are selected to verify the model constructed in this paper. The results show that the model has good applicability and advancement for the evaluation problem in this paper. Besides, expanding the scale of flexible adjustment resources in the distribution network can effectively improve the investment efficiency of the distribution network.

The rest of this paper is organized as follows: Section 2 analyzes the investment direction of the distribution network and then selects the indexes that characterize the investment efficiency of the distribution network and constructs an evaluation index system for the investment efficiency of the distribution network for the high proportion of renewable energy. Section 3 builds a hybrid multiattribute decision-making model for distribution network investment efficiency. Section 4 selects typical regions to conduct an empirical analysis of the constructed multiattribute decision-making model. Section 5 summarizes the full paper and proposes an outlook for the future.

2. Evaluation Index System for Investment Efficiency of High-Proportion Renewable Energy Distribution Network

Distribution network investment for the high proportion of renewable energy has certain pertinence. According to the investment direction of the distribution network under the new situation, following the systematic, scientific, pertinent, and operational principles of the index system, the index system is constructed from the power supply guarantee capacity, comprehensive carrying capacity, and value creation capacity of the distribution network.

In terms of power supply guarantee capacity, considering the "14th Five-Year Plan" period, the domestic economy will maintain a medium-to-high speed growth, and it is necessary to moderately advance the development of the distribution network and continuously enhance the power supply guarantee capacity to meet the demand for electricity from economic and social development. From power supply quality, power supply line stability, and user satisfaction, three indexes are selected to characterize the investment efficiency of the distribution network. In addition, energy storage as an important link in the flexible adjustment of resources [23, 24], low frequency is also an important factor affecting the comprehensive carrying capacity of the distribution network.

With the rapid development of renewable energy, the penetration rate of distributed power generation and the proportion of electric energy in terminal energy consumption will continue to increase. The distribution network needs to have a strong comprehensive carrying capacity to meet the needs of full consumption of clean energy and flexible connection of diversified loads. Therefore, five indexes are selected, including the average load rate of main transformers, the average load rate of lines, the comprehensive line loss rate, the proportion of renewable energy, and the proportion of flexible adjustment resources to characterize the investment efficiency of the distribution network.

In terms of value creation capability, considering the characteristics of the new power system and the development direction of the distribution network in the future, three indexes are selected to characterize the investment efficiency of the distribution network: the intelligent and standardized allocation rate of the distribution network, the digital development index, and the technical level of the energy Internet, and considering the important position of the distribution network in the goal of energy structure optimization, selecting the index of the proportion of electric energy in the terminal energy reflects the value creation ability of the distribution network.

To sum up, the evaluation index system of distribution network investment efficiency for the high proportion of renewable energy obtained as shown shown in Table 1.

Among them, the proportion of electric energy in the value creation ability of the secondary index reflects the proportion of electric energy use in production activities to the total energy, the intelligent standardized configuration rate index of the distribution network represents the proportion of intelligent information equipment in the distribution network, and the digital development index reflects the level of digital information of the distribution network, which is scored by a third-party organization. The energy Internet technology level index reflects the Internet technology level of the distribution network and is scored by a third-party organization.

Table 1: Evaluation index system of distribution network investment efficiency for the high proportion of renewable energy.

	First-level index	Second-level index
Distribution network investment efficiency	Power supply guarantee capacityact (C_1)	Average power outage time for urban and rural users (C_{11})
		Comprehensive voltage pass rate (C_{12})
		$N-1$ pass rate (C_{13})
	Comprehensive carrying capacity (C_2)	The average load rate of main transformers (C_{21})
		The average load rate of lines (C_{22})
		The comprehensive line loss rate (C_{23})
		The proportion of renewable energy (C_{24})
		The proportion of flexible adjustment resources (C_{25})
	Value creation capacity (C_3)	The index of the proportion of electric energy (C_{31})
		The intelligent and standardized allocation rate of the distribution network (C_{32})
		The digital development index (C_{33})
		The technical level of the energy Internet (C_{34})

3. Investment Efficiency Evaluation Model of Distribution Networks

3.1. Determination of Weights of the Index. In this paper, the subjective and objective integrated weighting model is used to determine the weights of the index, the fuzzy BWM is used to determine the subjective weights of the evaluation index, the anti-entropy weight method is used to determine the objective weights of the index, and finally, the game combination weighting model is used to determine the integrated weights of the index.

3.1.1. Subjective Weight Determination Based on the Fuzzy BWM Method. The BWM first selects the best criterion and the worst criterion and then compares them with other indexes in pairs, thus simplifying the comparison times between the two indexes, reducing the risk of inconsistency, and ensuring the reliability of the results. However, the traditional BWM does not consider the problem of uncertainty.

In order to make the BWM can effectively solve the decision-making problem in an uncertain environment, the fuzzy Best-Worst Method (fuzzy BWM, FBWM) was proposed in 2017 [25–27]. This method has been widely used in the selection of automobile suppliers, evaluation of offshore oil projects, decision-making and improvement of enterprise development strategic goals, allocation of water resources, sustainable development of mining projects, production of landslide maps, and management of supply chains. Distribution network investment is also uncertain, so the fuzzy BWM is also suitable for calculating subjective weights of the distribution network investment efficiency evaluation index.

Assuming that the research object includes n index in total, experts or decision-makers can give the importance degree of the two indexes in the way of language grade evaluation based on their knowledge and experience, such as equal importance, weakly important, and absolutely important. Then, according to Table 2, the language grade evaluation results can be converted into a triangular fuzzy number, and fuzzy comparison matrix $\widetilde{A}$ can be obtained as shown in the following:

Table 2: Translation rules of language grade evaluation results.

Linguistic variables	Membership function
Equally important (EI)	(1, 1, 1)
Weakly important (WI)	(2/3, 1, 3/2)
Fairly important (FI)	(3/2, 2, 5/2)
Very important (VI)	(5/2, 3, 7/2)
Absolutely important (AI)	(7/2, 4, 9/2)

$$i\widetilde{A} = \begin{matrix} c_1 & c_2 & \cdots & c_n \end{matrix} \begin{bmatrix} \widetilde{a}_{11} & \widetilde{a}_{12} & \cdots & \widetilde{a}_{1n} \\ \widetilde{a}_{21} & \widetilde{a}_{22} & \cdots & \widetilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{a}_{n1} & \widetilde{a}_{n2} & \cdots & \widetilde{a}_{nn} \end{bmatrix}, \quad (1)$$

where $\widetilde{a}_{ij}$ is the fuzzy preference degree of criterion relative to criterion j, which can be represented by a triangular fuzzy number.

The specific steps of using FBWM to determine the weights of each evaluation index are as follows.

Step 1. Build the evaluation index system.

It is very important to reasonably determine the evaluation index system for the risk assessment of electricity price supervision faced by power grid enterprises. It should be able to represent the basic characteristics of electricity price supervision risks faced by power grid enterprises. The abstract evaluation index system of electricity price supervision risk faced by power grid enterprises with an index can be expressed as $\{c_1, c_2, \ldots, c_n\}$, In this paper, $n = 15$.

Step 2. Determine the best criterion and worst criterion.

On the basis of constructing the evaluation index system, it is necessary to determine the best criterion c_B and the worst criterion c_W according to the knowledge and experience of decision-makers.

Step 3. Pairwise fuzzy preference comparison is made between the best criterion and each criterion.

Decision-makers compare the importance of each criterion in the best criterion and evaluation index system in pairs, give the language evaluation grade according to

Table 2, and then convert it into a triangular-fuzzy-numbers to construct a fuzzy best comparison vector $\widetilde{A}_B$.

$$\widetilde{A}_B = (\widetilde{a}_{B1}, \widetilde{a}_{B2}, \ldots, \widetilde{a}_{Bn}), \tag{2}$$

where $\widetilde{a}_{Bj}$ is the comparison result of the importance of the best criterion c_B and the criterion j, $j = 1, 2, \ldots, n$, and $\widetilde{a}_{BB} = (1, 1, 1)$.

Step 4. Pairwise fuzzy preference comparison between each criterion and the worst criterion.

Decision-makers compare the importance of each criterion in the worst criterion and evaluation index system in pairs and give the language evaluation grade according to Table 2 to construct a fuzzy worst comparison vector $\widetilde{A}_W$:

$$\widetilde{A}_W = (\widetilde{a}_{1W}, \widetilde{a}_{2W}, \ldots, \widetilde{a}_{nW}), \tag{3}$$

where $\widetilde{a}_{iW}$ is the comparison result of the importance degree between criterion i and the worst criterion c_W, $i = 1, 2, \ldots, n$, and $\widetilde{a}_{WW} = (1, 1, 1)$.

Step 5. Determine the optimal fuzzy weights value of each criterion $(\widetilde{w}_1^*, \widetilde{w}_2^*, \ldots, \widetilde{w}_n^*)$.

The ratio between the optimal fuzzy weight $\widetilde{w}_B$ of the best criterion and the optimal fuzzy weight $\widetilde{w}_j$ of each criterion should be as consistent as possible with the optimal fuzzy comparison vector $\widetilde{A}_B$, and the optimal fuzzy weight $\widetilde{w}_j$ of each criterion and the optimal fuzzy weight $\widetilde{w}_W$ of the worst criterion should be as consistent as possible with the optimal fuzzy comparison vector $\widetilde{A}_W$. According to this principle, the min-max problem with constraints can be constructed as shown in the following equationfd4:

$$\min \max_j \left\{ \left| \frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj} \right|, \left| \frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW} \right| \right\}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} R(\widetilde{w}_j) = 1, \\ l_j^w \le m_j^w \le u_j^w, \\ l_j^w \ge 0, \\ j = 1, 2, \ldots, n, \end{cases} \tag{4}$$

where
$\widetilde{w}_B = (l_B^w, m_B^w, u_B^w)$, $\widetilde{w}_j = (l_j^w, m_j^w, u_j^w)$, $\widetilde{w}_W = (l_W^w, m_W^w, u_W^w)$, $\widetilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, and $\widetilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$.

$R(\widetilde{w}_j)$ is used to convert the fuzzy weight value of criterion j into an accurate value, which can be calculated by

$$R(\widetilde{w}_j) = \frac{l_j^w + 4m_j^w + u_j^w}{6}. \tag{5}$$

Equation (4) can be transformed into a nonlinear constrained optimal problem as shown in the following:

$$\min \widetilde{\xi}$$

$$\text{s.t.} \begin{cases} \left| \frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj} \right| \le \widetilde{\xi}, \\ \left| \frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW} \right| \le \widetilde{\xi}, \\ \sum_{j=1}^{n} R(\widetilde{w}_j) = 1, \\ l_j^w \le m_j^w \le u_j^w, \\ l_j^w \ge 0, \\ j = 1, 2, \ldots, n, \end{cases} \tag{6}$$

where $\widetilde{\xi} = (l^\xi, m^\xi, u^\xi)$. Since $l^\xi \le m^\xi \le u^\xi$, let $\widetilde{\xi}^* = (k^*, k^*, k^*)$, where $k^* \le l^\xi$; then, equation (6) can be transformed into

$$\min \widetilde{\xi}^*$$

$$\text{s.t.} \begin{cases} \left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \le (k^*, k^*, k^*), \\ \left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \le (k^*, k^*, k^*), \\ \sum_{j=1}^{n} R(\widetilde{w}_j) = 1, \\ l_j^w \le m_j^w \le u_j^w, \\ l_j^w \ge 0, \\ j = 1, 2, \ldots, n. \end{cases} \tag{7}$$

By solving equation (7), the optimal fuzzy weights value of each criterion can be obtained, which are the final fuzzy weights of each evaluation index $W = (\widetilde{w}_1^*, \widetilde{w}_2^*, \ldots, \widetilde{w}_n^*)$.

When using the fuzzy Best-Worst Method to determine the weights of the index, it is necessary to test the consistency of fuzzy comparison of pairwise indexes, and index

consistency ratio (CR) is usually used for the judgment. The specific calculation is shown in the following equationfd8:

$$CR = \frac{R(\tilde{\xi}^*)}{CI}, \tag{8}$$

where $R(\tilde{\xi}^*)$ is the exact value of $\tilde{\xi}^*$ and CI is the consistency index of the fuzzy BWM method, which can be determined according to different values of $\tilde{a}_{BW}$ and Table 3.

3.1.2. Calculation of Objective Weights Based on the Anti-Entropy Weight Method. Objective weight vector w_1 is determined by the anti-entropy weight method. Entropy is a concept in system thermodynamics, which was later introduced into information theory. It is a measure of the disorder degree of a system [28–30]. When there are kinds of possible states in the system, and each possible state occurs with the probability of $p_j\,(j = 1, 2, \ldots, \mathrm{m})$, the entropy can be defined as the following expression:

$$h = -\sum_{j=1}^{m} p_j \ln p_j, \tag{9}$$

where $0 \le p_j \le 1$ and $\sum p_j = 1$.

Under the anti-entropy method, for the evaluation problem, the evaluation object is m, the number of indexes is n, the index value is $x_{ij}\,(i = 1, 2, \ldots, n, j = 1, 2, \ldots, m)$, and the evaluation matrix is $X = [x_{ij}]_{n\times m}$. We calculate the antientropy value of each criterion through the above data, as shown in

$$h_i = -\sum_{j=1}^{m} r_{ij} \ln\left(1 - r_{ij}\right), \tag{10}$$

where $r_{ij} = x_{ij}/\sum x_{ij}$.

Then, the final objective weight value w_{1i} of each criterion can be determined through normalization of the calculated antientropy value, as shown in the following:

$$w_{1i} = \frac{h_i}{\sum_i h_i}. \tag{11}$$

3.1.3. Comprehensive Weight Calculation Based on Game Theory. Considering the data dependence of the objective weighting method and the subjectivity of the subjective weighting method, this part uses the game theory combination weight method to determine the index weight [31]. On the one hand, it can avoid the excessively subjective situation of experts' experience judgment, and on the other hand, it can avoid the unreasonable situation of weight distribution caused by ignoring index attributes in objective weight assignment so as to obtain a more effective index weight.

In this paper, the basic principle of subjective and objective weight combination is to minimize the heterogeneity between subjective and objective weight results. The combination weighting method, which simply averages subjective and objective weights, can reduce the heterogeneity of subjective and objective weights to some extent, but it cannot minimize the heterogeneity. Therefore, this part applies the game theory to the combination process of subjective and objective weights and can fully consider the role of the results of single-subjective weights and a single-objective weight in the evaluation process, to balance the difference of a single weight through a reasonable weight distribution coefficient. The basic steps of the combination weighting method based on game theory are as follows.

Assuming that the weight vector $W_l = (w_{1,l}, w_{2,l}, \ldots, w_{n,l})\,(l = 1, 2, \ldots, L)$ of n index can be calculated by using L weighting methods, the basic weight set $W = \{W_1, W_2, \ldots, W_L\}$ can be obtained. The combined weights W_{inte} is defined as the linear combination of L basic weights, namely,

$$W_{\mathrm{inte}} = \sum_{l=1}^{L} \alpha_l \times W_l, \tag{12}$$

where α_l is the distribution coefficient of the l-th basic weights; it can be seen that there are infinite linear combinations of L basic weights.

In order to find the optimal combination weight $W_{\mathrm{inte}} r^*$, this part uses the idea of game theory to optimize the basic weight distribution coefficient in equation (12). The optimization goal is to minimize the heterogeneity (deviation) between the optimal combination weight and all basic weights, which can be expressed as

$$\min \sum_{l=1}^{L} \left\| \left(\sum_{l=1}^{L} \alpha_l \times W_l \right) - W_{l\,2} \right\|, \tag{13}$$

where $\|U\|$ represents the binary norm of vector U and α_l is the variable to be decided and $\sum \alpha_l = 1$.

The advanced commercial solver of MATLAB can be used to calculate the optimal value α_l^* of equation (13), and then, the combination weights based on game theory can be expressed as

$$W_{\mathrm{inte}}^* = \sum_{l=1}^{L} \alpha_l^* \times W_l. \tag{14}$$

In this paper, there are two basic weights to be combined: W_1 is the objective weight based on the anti-entropy weight method, and W_2 is the subjective weight based on fuzzy BWM. The deviation between the combined weight and the subjective and objective weight is minimum so that the criterion importance reflected by the subjective weights and the objective weights can be balanced. That is, the combined weight can not only reflect the attributes of the index itself but also effectively use the original data information of the index.

3.2. MARCOS Attribute Integration Method Based on Weighted Mahalanobis Distance. MARCOS is an attribute integration method proposed by Stević et al. in 2020 [32]. In this method, the utility function of the alternative scheme is determined by comparing the reference value of

Table 3: Consistency index (CI) for fuzzy BWM.

Linguistic variables	Equally important (EI)	Weakly important (WI)	Fairly important (FI)	Very important (VI)	Absolutely important (AI)
$\tilde{a}_{BW}$	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(7/2, 4, 9/2)
CI	3.00	3.80	5.29	6.69	8.04

the alternative scheme with the ideal weight, and the compromise ranking associated with the perfect scheme and the ideal negative scheme is realized, where the utility function represents an alternative's position on ideal and negative ideal solutions. MARCOS is a very reasonable method, which considers both ideal solution and negative ideal solution, closely determines the utility degree related to the two solutions, and considers the possibility of a large number of standards and alternatives while maintaining the stability of the method, so that the results have good robustness and accuracy. The specific steps are as follows.

Step 6. Form an initial decision matrix. Constructing a multi-index model including a set of N indexes and M alternatives, meanwhile, in the case of group decision-making, a group composed of R experts is established to score the alternatives according to the standards. In this case, the expert evaluation matrix is aggregated into the initial group decision matrix.

Step 7. Form the extended initial matrix $X = [x_{ij}]_{m\times n}$. Defining ideal (AI) and negative ideal (AAI) solutions to realize the extension of the initial matrix, ideal solution (AI) is the scheme with the best properties and negative ideal solution (AAI) is the worst scheme.

$$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \cdots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{pmatrix} \end{array}. \tag{15}$$

According to the nature of the standard, the values of AAI and AI are as follows:

$$\begin{aligned} AAI &= \min_i x_{ij}, if\ j \in B, \\ &\max_i x_{ij}, \text{if } j \in C, \\ AI &= \max_i x_{ij}, \text{if } j \in B, \\ &\min_i x_{ij}, if\ j \in C, \end{aligned} \tag{16}$$

where B represents a positive index and C represents a negative index.

Step 8. Standardize the extended initial matrix $N = [n_{ij}]_{m\times n}$. The normalized decision matrix is obtained by the initial normalization of the matrix.

$$\begin{aligned} n_{ij} &= \frac{x_{ij}}{x_{ai}}, if\ j \in B, \\ n_{ij} &= \frac{x_{ai}}{x_{ij}}, if\ j \in C, \end{aligned} \tag{17}$$

where x_{ij} and x_{ai} are the elements of the initial matrix $X = [x_{ij}]_{m\times n}$.

Step 9. Determine the weighted normalized decision matrix $V = [v_{ij}]_{m\times n}$. By multiplying the normalized decision matrix elements by the weights,

$$v_{ij} = n_{ij} \times w_j. \tag{18}$$

Step 10. Calculate the utility degree of the alternative K_i. The utility degree of the alternative scheme relative to the negative ideal and the ideal solution is calculated by the weighted Mahalanobis distance.

Mahalanobis distance is a statistical distance proposed by Mahalanobis, an Indian statistician, in 1936. This distance is independent of the measurement scale and is not affected by the dimension between coordinates [33–35]. It measures the relationship between two random variables by introducing the covariance of two random variables and eliminating the correlation between attribute indexes. The application of Markov distance substitution in the MARCOS method can effectively solve the related problems between attribute indexes. The equation for calculating the Mahalanobis distance between X and Y is

$$d(X,Y) = \sqrt{(X-Y)^T \sum^{-1} (X-Y)}, \tag{19}$$

where $\sum$ is the covariance matrix between the attribute indicator.

Although Mahalanobis distance takes into account the correlation between index attributes, it only takes into account the covariance between attribute indexes and the properties of covariance and variance are the same. The result represents the comprehensive degree of the deviation of the two attributes to their respective mean values. Therefore, the covariance inverse matrix in Mahalanobis distance may lead to unstable calculation results, which can easily magnify the influence between attributes, cannot accurately represent the degree of association between the two attributes, and ignore the differences between the attributes. Based on this, a weighted Mahalanobis distance using the Pearson correlation coefficient instead of

covariance is proposed in this paper. The weight in the weighted Mahalanobis distance is determined by the combination weighting method proposed in this section.

The calculation equation of weighted Mahalanobis distance is

$$d(X,Y) = \sqrt{(X-Y)^T \Omega^T \sum^{-1} \Omega (X-Y)}, \tag{20}$$

$$\Omega = \mathrm{diag}\left(\sqrt{\omega_1}, \sqrt{\omega_2}, \cdots, \sqrt{\omega_n}\right), \tag{21}$$

where $\sum$ is the Pearson correlation coefficient between the attribute indicator.

The advantages of weighted Mahalanobis distance compared with Euclidean distance are as follows:

(1) The calculation of Euclidean distance has strong limitations. The attributes of each factor in the data set that it can calculate must be independent of each other, while the calculation of weighted Mahalanobis distance is not limited by the correlation between factor attributes. When the factor attributes in the data set are independent of each other, the weighted Mahalanobis distance is equivalent to weighing and standardizing the calculated data. When there is correlation between factor attributes in the data set, the factors are linearly transformed and the data set is transformed into an attribute independent data set. At this time, the distance calculation is transformed into Euclidean distance calculation. Therefore, Euclidean distance is only a particular form of weighted Mahalanobis distance.

(2) Euclidean distance is easily affected by dimension. Weighted Mahalanobis distance standardizes the data and is not affected by dimension.

(3) Euclidean distance regards the attributes of factors as consistent, which deviates greatly from the actual situation of multiobjective investment decision-making. When making power grid planning investment decisions, different indexes have a different impact on the project. According to the needs of enterprises, the importance of the same index in the same project will change due to the diverse needs of enterprises. Weighted Mahalanobis distance can well reflect the contribution degree of influential factors in distribution network investment efficiency by using the F-BWM-anti-entropy weight method. Specifically, the greater the contribution degree, the greater the weight value of the influential factors.

We calculate the distance $d(A_i, S^+)$ from the i-th evaluation object to the positive ideal solution $d(A_i, S^+)$ and the distance $d(A_i, S^-)$ to the negative ideal solution S^- respectively, and the equation is as follows:

$$d(A_i, S^+) = \sqrt{(x_i - S^+)^T \Omega^T \sum^{-1} \Omega (x_i - S^+)}, \tag{22}$$

$$d(A_i, S^-) = \sqrt{(x_i - S^-)^T \Omega^T \sum^{-1} \Omega (x_i - S^-)}. \tag{23}$$

Step 11. Determine the utility function of alternative $f(K_i)$. The utility function is a compromise between alternative and ideal and anti-ideal solutions. Specific expressions are as follows:

$$f(K_i) = \frac{d(A_i, S^+) + d(A_i, S^-)}{1 + 1 - f(d(A_i, S^+))/f(d(A_i, S^+)) + 1 - f(d(A_i, S^-))/f(d(A_i, S^-))}, \tag{24}$$

where $f(K_i{}^-)$ represents the utility function related to the negative ideal solution, and $f(K_i{}^+)$ represents the utility function related to the ideal solution. The utility function expression is as follows:

$$\begin{aligned} f(K_i{}^+) &= \frac{d(A_i, S^-)}{d(A_i, S^+) + d(A_i, S^-)}, \\ f(K_i{}^-) &= \frac{d(A_i, S^+)}{d(A_i, S^+) + d(A_i, S^-)}. \end{aligned} \tag{25}$$

Step 12. Rank the alternatives. The order of alternatives is based on the final value of the utility function. Finally, the ideal situation is that the alternative has the highest possible utility function value.

The framework of mixed multiattribute decision model empirical analysis in this paper is shown in Figure 1.

4. Empirical Analysis

4.1. Case Overview. Taking the investment of 8 regional distribution networks in a province of China in 2021 as an example, the investment efficiency is evaluated. The basic data of each distribution network are shown in Table 4. According to Table 4, two characteristic indexes, the proportion of renewable energy installed capacity and the proportion of flexible adjustment resources, are selected for analysis as follows:

(1) Cases 3, 4, 5, and 8 have a relatively low proportion of installed renewable energy. Within the range of 20% to 50%, they belong to the development stage of

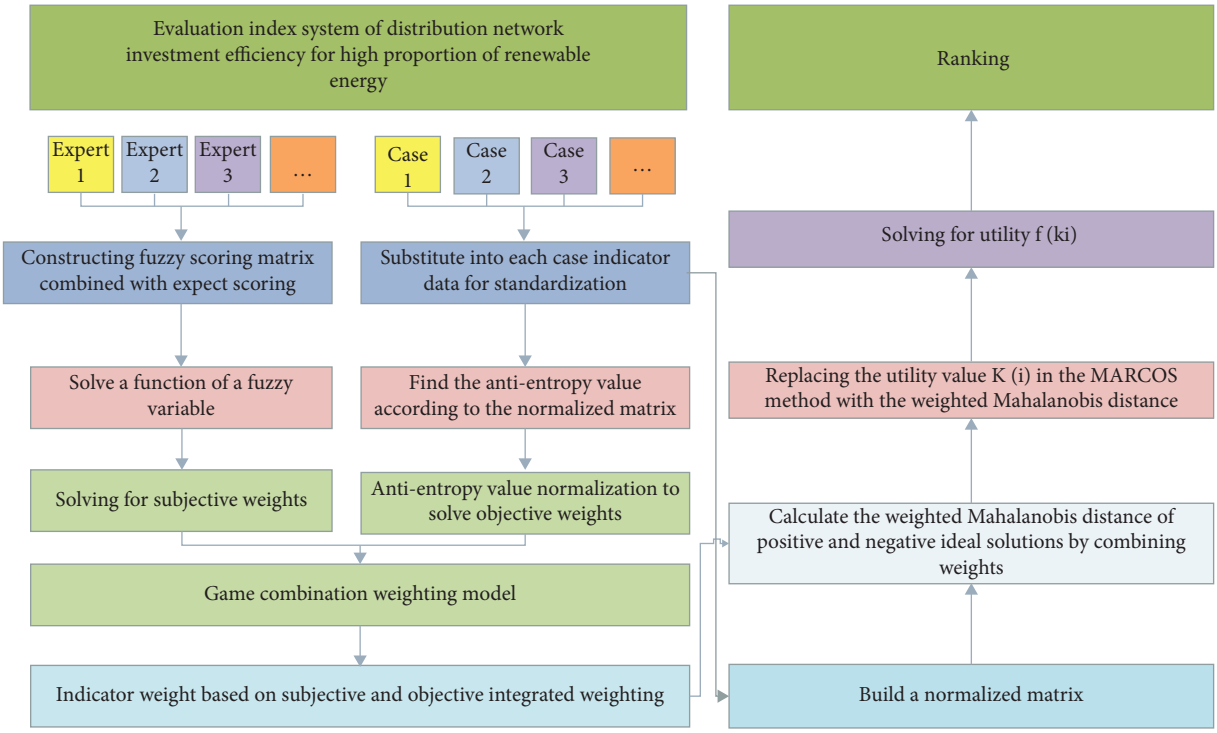

Figure 1: The framework of mixed multiattribute decision model empirical analysis.

renewable energy. Among them, Case 4 has the lowest proportion of installed renewable energy, which was 20.56%; other cases accounted for 50%–70% of the installed capacity of renewable energy, which belonged to the advanced stage. Among them, the proportion of installed capacity of renewable energy in Case 6 was 67.87%, the highest.

(2) The flexibility adjustment resources of Cases 5 and 6 are relatively large, accounting for 14.40% and 14.87%, respectively, as shown in Figure 2.

4.2. Index Weighting Results. In this part, the fuzzy BWM is used to calculate the subjective weight, the anti-entropy weight method is used to calculate the objective weight of the index, and finally the integrated weight is obtained through the game combination.

4.2.1. Fuzzy BWM to Calculate Subjective Weight. First, according to the selection of all experts, among the three first-level indexes of power supply guarantee capability (C_1), comprehensive carrying capacity (C_2), and value creation capability (C_3), the optimal index is value creation capability (C_3), and the most optimal one is value creation capability (C_3). The inferior index is the power supply guarantee capability (C_1). The results of the comparison between the importance of these two indexes and other indexes are shown in Tables 5 and 6.

According to the comparison results of the optimal and worst indexes with each index, the fuzzy comparison vectors corresponding to the optimal and worst indexes are as follows:

$$\tilde{A}_B = \left[\left(\frac{7}{2}, 4, \frac{9}{2}\right), \left(\frac{3}{2}, 2, \frac{5}{2}\right), (1, 1, 1)\right],$$
$$\tilde{A}_W = \left[(1, 1, 1), \left(\frac{3}{2}, 2, \frac{5}{2}\right), \left(\frac{7}{2}, 4, \frac{9}{2}\right)\right]. \tag{26}$$

Combining equation (3) with the fuzzy comparison vectors corresponding to the optimal index and the worst index, the optimal fuzzy weight vectors of the four first-level indexes are obtained, which are as follows:

$$\tilde{w}_1^* = (0.134, 0.141, 0.163), \tilde{w}_2^* = (0.241, 0.0.276, 0.365), \tilde{w}_3^* = (0.567, 0.0.567, 0.596). \tag{27}$$

Table 4: Basic data of 8 distribution networks.

Index	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
C_{11}	3.20	2.50	2.30	3.10	0.80	2.50	1.20	0.70
C_{12}	96.56	98.17	98.23	95.56	100	99.05	99.34	98.67
C_{13}	95.12	97.17	99.50	95.34	100	99.78	100	99.56
C_{21}	40.67	45.34	50.45	78.45	60.56	50.45	50.45	55.67
C_{22}	50.54	54.23	55.45	76.45	62.45	45.78	55.56	60.45
C_{23}	8.89	8.34	6.43	8.67	3.45	4.78	4.56	4.34
C_{24}	65.56	54.34	34.67	20.56	30.78	67.87	66.56	45.67
C_{25}	10.56	8.37	5.46	3.56	14.40	14.87	9.67	5.46
C_{31}	35.09	30.78	33.67	27.80	37.70	40.32	43.56	44.67
C_{32}	78.78	70.56	80.34	67.45	78.67	76.78	75.56	77.57
C_{33}	65.45	64.23	59.37	57.23	59.89	45.67	68.67	69.67
C_{34}	75.56	74.23	72.34	65.34	65.67	65.79	81.34	75.78

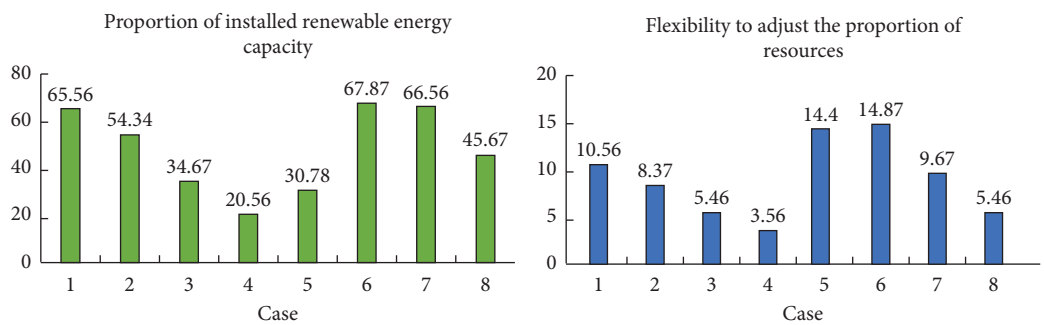

Figure 2: Case characteristic index values.

The optimal weight is obtained according to equation (7): $\tilde{w}_1^* = 0.14, \tilde{w}_2^* = 0.29$, and $\tilde{w}_3^* = 0.57$

The best and worst indexes of the evaluation indexes corresponding to the three first-level indexes are shown in Table 7.

Then, we compare the importance of the evaluation indexes of these three first-level indexes with the corresponding optimal and worst indexes. The results are shown in Tables 8 and 9.

According to the comparison results of Tables 8 and 9, the optimal and worst fuzzy comparison vectors of the evaluation indexes of the three first-level indexes can be obtained as follows.

The optimal and worst fuzzy comparison vector corresponding to the three evaluation indexes of power supply guarantee capability (C_1) are as follows:

$$\tilde{A}_B = \left[\left(\frac{5}{2}, 3, \frac{7}{2}\right), \left(\frac{2}{3}, 1, \frac{3}{2}\right), (1, 1, 1)\right],$$
$$\tilde{A}_W = \left[(1, 1, 1), \left(\frac{3}{2}, 2, \frac{5}{2}\right), \left(\frac{5}{2}, 3, \frac{7}{2}\right)\right]. \tag{28}$$

The optimal fuzzy weight vector of the second-level index of the power supply guarantee capability index is obtained, as follows:

$$\tilde{w}_1^* = (0.139, 0.163, 0.164), \tilde{w}_2^* = (0.272, 0.0.423, 0.426),$$
$$\tilde{w}_3^* = (0.376, 0.455, 0.455). \tag{29}$$

The optimal weight is obtained according to equation (7): $\tilde{w}_1^* = 0.16, \tilde{w}_2^* = 0.40, \tilde{w}_3^* = 0.44$

The optimal and worst fuzzy comparison vector corresponding to the five evaluation indexes of comprehensive carrying capacity (C_2) are as follows:

$$\tilde{A}_B = \left[\left(\frac{5}{2}, 3, \frac{7}{2}\right), \left(\frac{5}{2}, 3, \frac{7}{2}\right), \left(\frac{7}{2}, 4, \frac{9}{2}\right), \left(\frac{7}{2}, 4, \frac{9}{2}\right), (1, 1, 1)\right],$$
$$\tilde{A}_W = \left[\left(\frac{2}{3}, 1, \frac{3}{2}\right), \left(\frac{2}{3}, 1, \frac{3}{2}\right), (1, 1, 1), \left(\frac{5}{2}, 3, \frac{7}{2}\right), \left(\frac{7}{2}, 4, \frac{9}{2}\right)\right]. \tag{30}$$

The optimal fuzzy weight vectors of the five secondary indexes of the comprehensive carrying capacity index are obtained, as follows:

$$\tilde{w}_1^* = (0.109,\ 0.117,\ 0.134), \tilde{w}_2^* = (0.134, 0.0.134, 0.134),$$
$$\tilde{w}_3^* = (0.086, 0.095, 0.105), \tilde{w}_4^* = (0.144, 0.165, 0.204), \tilde{w}_5^* = (0.485, 0.485, 0.485). \tag{31}$$

Table 5: Comparison of the importance of the optimal index with other indexes.

Index	Best index C_3
C_1	AI
C_2	FI

Table 6: Comparison of the importance of other indexes and the worst index.

Index	Worst index C_1
C_2	FI
C_3	AI

Table 7: The best and worst indexes of the evaluation indexes corresponding to the three first-level indexes.

Evaluated indexes	Evaluation indexes	
	Best index	Worst index
C_1	C_{13}	C_{11}
C_2	C_{25}	C_{23}
C_3	C_{31}	C_{34}

The optimal weight is obtained according to equation (7): $\tilde{w}_1^* = 0.12, \tilde{w}_2^* = 0.13, \tilde{w}_3^* = 0.10$, $\tilde{w}_4^* = 0.17$, and $\tilde{w}_5^* = 0.48$.

The optimal fuzzy weight vector for the four evaluation indexes of value creation capability (C_3) is obtained are as follows:

$$\begin{aligned} \tilde{A}_B &= \left[(1,1,1), \left(\frac{2}{3}, 1, \frac{3}{2}\right), \left(\frac{2}{3}, 1, \frac{3}{2}\right), \left(\frac{3}{2}, 2, \frac{5}{2}\right)\right], \\ \tilde{A}_W &= \left[\left(\frac{3}{2}, 2, \frac{5}{2}\right), \left(\frac{2}{3}, 1, \frac{3}{2}\right), \left(\frac{2}{3}, 1, \frac{3}{2}\right), (1,1,1)\right]. \end{aligned} \tag{32}$$

The optimal fuzzy weight vectors of the four secondary indexes of the value creation capability index are obtained, as follows:

$$\begin{aligned} &\tilde{w}_1^* = (0.256,\ 0.333,\ 0.333), \tilde{w}_2^* = (0.191, 0.256, 0.263), \\ &\tilde{w}_3^* = (0.185, 0.256, 0.263), \tilde{w}_4^* = (0.146, 0.196, 0.198). \end{aligned} \tag{33}$$

The optimal weight is obtained according to equation (7): $\tilde{w}_1^* = 0.32, \tilde{w}_2^* = 0.25, \tilde{w}_3^* = 0.24$, and $\tilde{w}_4^* = 0.1$

Finally, the subjective weight results of the indexes are summarized as shown in Table 10.

4.2.2. Objective Weight Based on the Anti-Entropy Weight Method. For the eight distribution networks to be evaluated, based on the index values of each case, according to equations (9) and (10), the anti-entropy weight method objective weight of each index is calculated, as shown in Table 11.

4.2.3. Determination of Subjective and Objective Integration Weights. Based on the objective weight w_{1i} and the subjective weight w_{2i}, equation (13) is solved to obtain $\alpha_1^* = 0.5824$, and $\alpha_2^* = 0.4176$. Therefore, the combined weight result is based on game theory as shown in Table 12.

Table 8: Comparison of the importance of the optimal index with other indexes.

	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}	C_{32}	C_{33}	C_{34}
C_{13}	VI	WI	—	—	—	—	—	—	—
C_{25}	—	—	VI	VI	AI	WI	—	—	—
C_{31}	—	—	—	—	—	—	WI	WI	FI

Table 9: Comparison of the importance of other indexes and the worst index.

	C_{11}	C_{23}	C_{34}
C_{12}	FI	—	—
C_{13}	VI	—	—
C_{21}		WI	—
C_{22}		WI	—
C_{24}		VI	—
C_{25}	—	AI	—
C_{31}	—	—	FI
C_{32}	—	—	WI
C_{33}	—	—	WI

The weight calculation results are shown in Figure 3, and the analysis can be obtained: the subjective fluctuation of the fuzzy BWM is large, and the fluctuation of the anti-entropy weight method is small, which is not completely consistent with the results of the game theory. The weight values calculated based on the game theory combination weighting are all between the two single evaluation weight results, and the combined weight coefficient improves the problem of the high-frequency extreme value span of the subjective method weight results and, at the same time, flexes the result of the objective evaluation. Considering the subjective influence of external factors, the evaluation results are more accurate and reasonable, and the dominant role of a single evaluation is avoided to the greatest extent.

The five indicators with the largest weights in the game theory portfolio weights are as follows: the proportion of electric energy in terminal energy, the proportion of flexible adjustment resources, the standardization and intelligent coverage of the distribution network, the level of digital development, and the level of energy Internet technology, respectively, accounted for 0.1396, 0.1205, 0.1156, 0.1127, and 0.0958. Among them, four indicators reflect the value creation capacity of the distribution network, and one indicator reflects the comprehensive carrying capacity of the distribution network. It shows that for the distribution network, the value creation ability can better characterize the investment efficiency of the distribution network. Specifically, with the high-quality development of the power grid and the integration of a high proportion of renewable energy into the grid, higher requirements have been placed on the value creation capability of the distribution network.

4.3. Comprehensive Evaluation Results. The original data of the selected eight distribution networks on each index are normalized, and combined with the index weighting results,

Table 10: Subjective weight results of indexes.

Index	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{31}	C_{32}	C_{33}	C_{34}
Subjective weight	0.0224	0.056	0.0616	0.0348	0.0377	0.029	0.0493	0.1392	0.1824	0.1425	0.1368	0.1083
Ranking	12	7	6	10	9	11	8	3	1	2	4	5

Table 11: Objective weight of each index.

Index	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{31}	C_{32}	C_{33}	C_{34}
Objective weight	0.0965	0.0778	0.0779	0.0815	0.0798	0.0877	0.0889	0.0945	0.0799	0.0781	0.0791	0.0783
Ranking	1	12	11	5	7	4	3	2	6	10	8	9

Table 12: Combined weight of each index.

Index	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{31}	C_{32}	C_{33}	C_{34}
Combined weight	0.0533	0.0651	0.0684	0.0543	0.0553	0.0535	0.0658	0.1205	0.1396	0.1156	0.1127	0.0958
Ranking	12	8	7	10	9	11	6	2	1	3	4	5

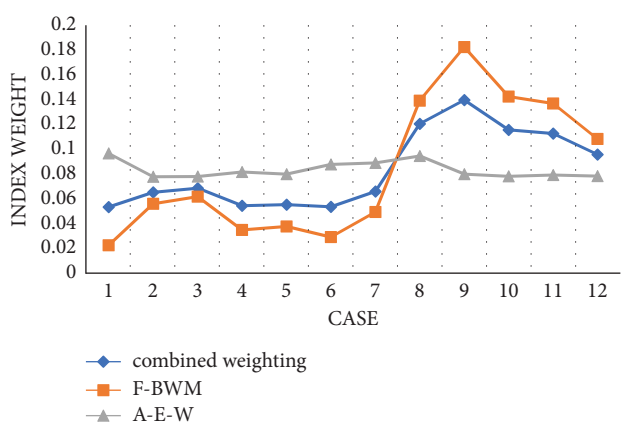

Figure 3: Comparison of the weight results.

the weighted normalization decision matrix of the distribution network is calculated as shown in Table 13.

According to Table 13, the positive ideal solution and negative ideal solution are obtained as shown in Table 14.

Based on the weighted normalized decision matrix, equations (19) and (20) are used to determine the weighted Mahalanobis distance-based trade-off between MARCOS for alternatives and ideal and anti-ideal solutions, and equation (22) is used to calculate the relative positive and negative ideals of each distribution network The utility function result of the solution can be used to judge the investment efficiency of the distribution network. Table 15 shows the results of MARCOS investment efficiency evaluation of the distribution network based on weighted Mahalanobis distance.

The utility values of 8 cases are shown in Table 14. It can be seen that among the 8 cases, Case 5 has the highest utility value, indicating that Case 5 has the highest investment efficiency, followed by Case 6. Case 2 has the lowest utility value, indicating that its investment efficiency is poorer in the eight cases. Among them, Case 5 has the best performance in terms of indicators C_{12}, C_{13}, C_{21}, C_{22}, and C_{23}. Combining indicators C_{24} and C_{25}, when the proportion of renewable energy installed capacity is relatively low and the proportion of flexible adjustment resources is relatively high, the distribution network has better power supply guarantee capacity and comprehensive carrying capacity, so the investment efficiency of the distribution network in Case 5 is the best. On the contrary, in Case 2, the proportion of installed capacity of renewable energy is relatively high, and the proportion of flexible adjustment resources is relatively low, resulting in poor power supply guarantee capacity and comprehensive carrying capacity and its overall low-value creation capacity. Therefore, the investment efficiency of Case 2 is the lowest.

4.4. Validity Test. In order to verify the validity of the distribution network investment efficiency evaluation model constructed in this paper, this paper takes the three models as a comparative reference and carries out the model ranking consistency test and sample separation test. The set comparison models are shown in Table 16, where Model 1 is the model proposed in this paper.

4.4.1. Sequence Consistency Check. Ranking consistency is an important indicator reflecting the robustness of multi-attribute decision-making methods. This paper constructs the following ranking consistency index:

$$r_s = 1 - \frac{6 \times \sum_{i=1}^{N} (x_i - y_i)^2}{N \times (N^2 - 1)},$$

$$r_w = 1 - \frac{6 \times \sum_{i=1}^{N} (x_i - y_i)^2 [(N - x_i + 1)(N - y_i + 1)]}{N \times (N^3 + N^2 - N - 1)}, \quad (34)$$

$$WS = 1 - \sum_{i=1}^{N} \left(2^{-x_1} \times \frac{|x_i - y_i|}{\max\{|x_i - 1|, |x_i - N|\}} \right).$$

In the equation, x and y represent the two sorting results, and N represents the number of alternatives in the sorting. The higher the obtained correlation coefficient, the closer the ranking results between the schemes are.

Table 13: Distribution network weighted normalization decision matrix.

Index	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	vi+	vi−
C_{11}	0.0117	0.0149	0.0162	0.0120	0.0467	0.0149	0.0311	0.0533	0.0533	0.0117
C_{12}	0.0629	0.0639	0.0640	0.0622	0.0651	0.0645	0.0647	0.0642	0.0651	0.0622
C_{13}	0.0651	0.0665	0.0681	0.0652	0.0684	0.0683	0.0684	0.0681	0.0684	0.0651
C_{21}	0.0368	0.0410	0.0457	0.0485	0.0543	0.0457	0.0457	0.0504	0.0543	0.0368
C_{22}	0.0466	0.0500	0.0511	0.0506	0.0553	0.0422	0.0512	0.0553	0.0553	0.0422
C_{23}	0.0208	0.0221	0.0287	0.0213	0.0535	0.0386	0.0405	0.0425	0.0535	0.0208
C_{24}	0.0636	0.0527	0.0336	0.0199	0.0299	0.0658	0.0646	0.0443	0.0658	0.0199
C_{25}	0.0856	0.0678	0.0443	0.0289	0.1167	0.1205	0.0784	0.0443	0.1205	0.0289
C_{31}	0.1097	0.0962	0.1052	0.0869	0.1178	0.1260	0.1361	0.1396	0.1396	0.0869
C_{32}	0.1134	0.1015	0.1156	0.0971	0.1132	0.1105	0.1087	0.1116	0.1156	0.0971
C_{33}	0.1059	0.1039	0.0960	0.0926	0.0969	0.0739	0.1111	0.1127	0.1127	0.0739
C_{34}	0.0890	0.0874	0.0852	0.0769	0.0773	0.0775	0.0958	0.0892	0.0958	0.0769

Table 14: Positive and negative ideal solutions.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
$k\ (j)+$	440.15	128.78	178.71	289.33	685.03	462.93	330.72	268.41
$k\ (j)-$	1259.93	922.27	697.11	431.17	483.55	1092.54	1152.95	737.28

Table 15: Results of case utility.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Utility degree	0.5019	0.2412	0.3810	0.5460	0.7473	0.5845	0.4895	0.5553
Ranking	5	8	7	4	1	2	6	3

Based on the basic data of the above eight distribution networks on each index, the ranking results of the investment efficiency evaluation of the eight distribution networks under each comparison model are obtained, and the ranking consistency of the three comparison models relative to Model 1 is calculated. The results are shown in Table 17.

Analysis of Table 16 shows that there is inconsistency in the model ranking. There are two main reasons for this. First, the model weights are inconsistent. The model used in this paper is Model 1, while Model 2 and Model 3 only use the subjective weighting method and the objective weighting method to determine the weights, so the large difference in weights leads to low-ranking consistency. In Model 2, only the fuzzy BWM subjective weighting method is used to calculate the weight, and the original information in the indicators is not considered, resulting in a large difference in the weight of the two methods, so the ranking results are quite different. For example, Case 2 is ranked 8 in Model 1. Meanwhile, Case 2 is ranked 2 in Model 2. In Model 3, the weight of the anti-entropy weight method is used. Still, as an objective weighting method, the anti-entropy weight method pays too much attention to the difference between the index data and ignores the meaning of the index itself. And it cannot reflect the interaction between the various indicators in the distribution network investment efficiency evaluation index system. Thus, the sorting results are also quite different from Model 1. Second, the evaluation method adopted by Model 4 is different from that of Model 1. Model 1 uses the Pearson coefficient instead of the weighted Mahalanobis distance of the covariance matrix, and Model 4 uses the ordinary Mahalanobis distance. The inverse covariance matrix in the ordinary Mahalanobis distance may cause inconsistent calculation results, amplify the influence between attributes, and cannot accurately represent the degree of correlation between two attributes, and the differences between the attributes are indeed ignored, so the sorting results of the two are inconsistent.

Specifically, we analyze the selected three consistency indicators, r_s and r_w are symmetry indicators, WS is asymmetric indicators, among them, the WS index is the asymmetric index, which is more accurate for judging the consistency of the model ranking. It can be seen from the table that r_s and r_w of model 1, model 2 and model 3 are quite different, but the first ranking is Case 5, so WS is relatively close, 0.6493 and 0.8572, respectively. Compared with model 4, the value of WS is also greater than 0.5, so in general, the ranking results of the comparison model have a certain consistency with the ranking results of the model proposed in this paper.

4.4.2. Sample Resolution. The degree of sample separation is an important method for judging the validity of the ranking results of the multiattribute decision-making model. It is usually judged by the sensitivity (η) index. The larger the obtained index value, the better the sample separation degree of the model. The specific calculation equation is as follows:

$$\eta = \frac{\delta_{j,\max} - \delta_{j,\sec}}{\delta_{j,\max}}. \tag{35}$$

Among them, δ_j is the relative closeness of each alternative to the ideal solution, $\delta_{j,\max}$ and $\delta_{j,\min}$ are the maximum and minimum values of δ_j, and $\delta_{j,\sec}$ takes the ranking in δ_j the second value.

Table 16: Basic information of comparison models.

Model	Indicator weighting method	Property integration method
Model 1	FBWM-AEW-	I-M-MARCOS
Model 2	FBWM	I-M-MARCOS
Model 3	AEW	I-M-MARCOS
Model 4	FBWM-AEW	MARCOS

Table 17: Model ranking consistency test results.

		Model 1	Model 2	Model 3	Model 4
Sort results	A_1	5	4	5	2
	A_2	8	2	6	4
	A_3	7	3	7	7
	A_4	4	6	8	8
	A_5	1	1	1	5
	A_6	2	8	3	3
	A_7	6	7	2	2
	A_8	3	5	4	1
Consistency indicator	r_s	1.0000	−0.1667	0.5476	0.0714
	r_w	1.0000	−0.0450	0.6085	0.0582
	WS	1.0000	0.6493	0.8572	0.5219

Table 18: Sample separation test results.

	Model 1	Model 2	Model 3	Model 4
η	0.2785	0.0494	0.0167	0.0821

Based on the basic data on each index of the eight distribution networks, the index scores of the investment efficiency evaluation of each distribution network under each comparative model are obtained, and then the sample separation degree is calculated. The results are shown in Table 18.

As shown in the table, the sample separation degree of Model 1 is the largest among all contrasting models, i.e., the proposed FBWM-AEW-I-M-MARCOS model performs better in sample separation. Therefore, when the ranking results are not significantly different, adopting this attribute decision model has a stronger ability to distinguish alternatives in the ranking process. The FBWM-AEW-I-M-MARCOS model proposed in this paper can better improve decision-making efficiency on the premise of ensuring robustness.

5. Conclusions

The investment in the distribution network under the construction of a new power system accounts for more than 50% of the total investment in the power grid. Therefore, from the perspective of facing high proportion of renewable energy, it is of significant value to establish a new evaluation index system for the investment efficiency of the distribution network. Based on the requirements for a distribution network under the construction of a new power system, this paper analyzes the investment direction of the distribution network and constructs the evaluation index system of distribution network investment efficiency for high proportion of renewable energy and the mixed multiattribute data game model. Finally, eight distribution networks are taken as examples to analyze the calculation.

The results of this paper show that the distribution network investment oriented to high-proportion renewable energy is mainly used to solve the problems of high-proportion renewable energy grid connection, energy transformation, and energy interconnection. In the distribution network, the proportion of renewable energy, the proportion of flexible regulation resources, the proportion of electric energy to the terminal energy, the intelligent and standardized distribution rate of the distribution network, the digital development index, and the level of energy Internet technology have a significant impact on the above aspects, thus affecting the investment efficiency of the distribution network. The empirical results show that expanding the scale of flexible regulation resources in the distribution network, it can promote the consumption of renewable energy in the distribution network, further make the distribution network develop towards intelligence and informatization, and effectively improve the investment efficiency of the distribution network.

The hybrid multiattribute decision-making model constructed in this paper has good applicability for the evaluation of distribution network investment efficiency. On the one hand, the proposed method based on the fuzzy BWM and anti-entropy weight method can make full use of the original information of indexes and consider the correlation between indexes on the basis of reducing subjectivity so as to ensure the reliability of weight results. On the other hand, the proposed MARCOS multiattribute decision-making method based on improved weighted Mahalanobis distance overcomes the limitation of traditional Mahalanobis distance, and the MARCOS method has good applicability to evaluate the merits of multiple objects to be evaluated.

This paper studies the investment efficiency evaluation of distribution networks. The research shows that the proportion of renewable energy and the proportion of flexible adjustment resources in distribution networks are the key factors affecting the investment efficiency of the distribution

network. In the future, we can study the key relationship between different renewable energy penetrations and the investment efficiency of distribution networks, which is of great significance to the construction of a new power system and the realization of the carbon peak and neutrality goal in the future. In addition, the integrated energy system is an important field. The proposed method must be applied in such study objects. In the future, the impact of pipe networks on a high proportion of renewable distribution networks will be studied [36–38].

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Huiru Zhao and Guanglong Xie guided the research; Kerao Lin and Juhua Hong established the model and implemented the simulation; Lijia Li wrote this article; and Wangzhen Ma and Xuejie Wang checked the language.

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