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RESEARCH ARTICLE

Comprehensive Benefits Evaluation of Renewable Energy Based on Grey-DEMATEL and DQ-GRA

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ABSTRACT In the pursuit of the 'double carbon' goal, the vigorous development of renewable energy has been an inevitable trend in energy transformation. The evaluation on comprehensive benefits associated with renewable energy plans is crucial for the advancement and implementation of renewable energy. This paper constructed an appraisal index system from four main dimensions, including economic benefits, environmental benefits, energy consumption benefits, and social benefits. This paper also proposed a hybrid multi-criteria decision-making (MCDM) model based on grey decision-making trial and evaluation laboratory (grey-DEMATEL) and modified difference-quotient grey relational analysis (DQ-GRA). Firstly, we applied the grey-DEMATEL to calculate the indicator weights used in modified DQ-GRA. Then, to rank renewable energy plans for evaluation, the proposed modified DQ-GRA method was applied. Finally, utilizing ten distinct renewable energy plans in Fujian Province as the focal point of our investigation, we undertook a comprehensive evaluation and analysis employing the research methodology introduced in this paper and compared the proposed method with the entropy weight method to authenticate its efficacy, thus validating the reliability and accuracy of our approach.

INDEX TERMS Renewable energy, comprehensive benefits evaluation, grey-DEMATEL, DQ-GRA, hybrid MCDM framework.

I. INTRODUCTION

In light of the escalating concerns surrounding energy security, climate change, and environmental issues, the shift towards a low-carbon, clean, and sustainable energy landscape has emerged as the predominant trajectory in the worldwide energy transformation. The robust expansion of renewable energy sources has garnered unanimous support as a pivotal undertaking in this global energy transition [1], [2], [3]. Ever since the ratification of the Paris Agreement [4] and the publication of the IPCC's 'Special Report on Global Warming of 1.5°C' [5], an increasing number of nations have pledged to attain net-zero emissions targets. As of November 2023, approximately 145 countries have either declared their intention to achieve net-zero emissions or are actively contemplating such goals, collectively representing almost 90% of global emissions.

Viewed from a global context, renewable energy constitutes an intrinsic principle underpinning the evolution of the world's economy and represents a crucial prerequisite for the sustainable advancement of emerging technological revolutions. Considering the domestic development landscape, the adoption of renewable energy emerges as a pivotal strategy for China in its quest to ascend to the upper echelons of the global value chain and to transition into a novel epoch of economic progression [6], [7]. With the "14th Five-Year Plan", China is targeting carbon peak, carbon neutrality, and the 2035 long-term objectives. Efforts are being made to

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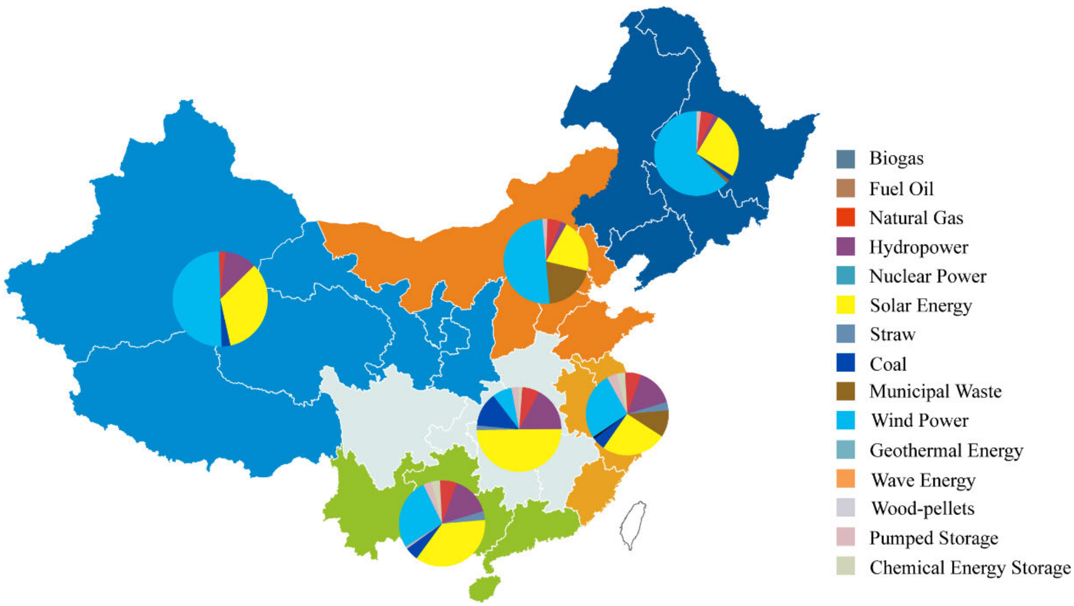

FIGURE 1. Installed capacity in 2050.

vigorously promote the exploration and application of renewable energy, and continuous breakthroughs are also being achieved.

Over the past couple of years, China's wind power, photovoltaic power as the representative of renewable energy has been effective, the installed capacity steadily ranked first in the world and continually achieved new breakthroughs. In the first three quarters of 2023, China installed 172 million kilowatts of new renewable energy, up 93 per cent year-on-year, accounting for 76 per cent of new installations. Among them, hydropower increased by 7.88 million kilowatts, wind power by 33.48 million kilowatts, photovoltaic power by 128.94 million kilowatts, and biomass power by 2.07 million kilowatts [8]. As of the end of October 2023, the installed capacity in the country surpassed 1.4 billion kilowatts, amounting to 1.404 billion kilowatts, with a year-on-year growth of 20.8%, accounting for approximately 49.9% of the country's total installed capacity. Specifically, hydropower accounts for 420 million kilowatts (including conventional hydropower at 370 million kilowatts and pumped storage hydropower at 50.04 million kilowatts), wind power for 404 million kilowatts, photovoltaic power for 536 million kilowatts, and biomass power for 44 million kilowatts [9].

The ''14th Five-Year Plan for Renewable Energy Development'' [10] proposes sustained and vigorous efforts in the exploitation of wind and photovoltaic power. It vigorously promote the bases exploitation in the ''Three North'' region, and actively promote the distributed exploitation in the central and southeastern regions. Promote the integrated exploitation of water, wind and solar integrated bases in the southwestern region, and actively promote the cluster development of offshore wind power in the eastern coastal areas. The report ''China 2050 High Renewable Energy Penetration Scenario and Roadmap Study'' [11] proposes that in the high proportion renewable energy scenario, the renewable energy planning and deployment (EDO) model has different optimized deployments for commercialized technologies under different renewable energy generation scenarios, which reflects the variety of geographical distribution and time distribution. Among them, onshore wind power plays a significant role, and offshore wind power is increasingly crucial in achieving high proportions of renewable energy generation. In solar energy technologies, ground-mounted photovoltaic power stations are more prominent compared to distributed solar energy generation like rooftop solar panels. In the high-proportion renewable energy scenario, Concentrated Solar Power (CSP) experiences rapid growth due to its higher adjustability with integrated heat storage capabilities. Biomass power occupies a place in the renewable energy. With the requirement of feedstock for bio-liquid fuels, it will change from agricultural and forestry residue power plants to municipal waste power plants. Geothermal and ocean energy, constrained by resource availability and economic factors, contribute relatively less compared to other sources. Nevertheless, their estimated potentials are fully explored. The installed capacity of renewable energy in each region in 2050 is shown in Fig. 1.

The comprehensive benefits evaluation can quantitatively analyze the rationality, reliability and economy of renewable energy, so as to accurately and effectively select renewable energy schemes, and can horizontally compare and evaluate different power generation technologies. It provides a rational reference for the industrial layout and provides strong support for the application and promotion of advanced technologies.

Recently, hybrid multi-criteria decision-making (MCDM) has come into the focus of experts, providing a flexible,

TABLE 1. Analytical comparison of different evaluation methods.

Method	Relevant literature	Subjective	Objective	Requirements for the data	Simple calculation	Others
DEMATEL	[13], [18], [20], [21], [22], [23], [24], [25]	√	×	×	√	When making judgments, facing issues such as insufficient information and uncertainty makes the judgment results more subjective.
GRA	[18], [19], [20], [21], [22], [23], [24], [26]	×	√	×	√	Need to determine the resolution
TOPSIS	[14], [23], [25], [27], [28], [29], [30]	×	√	×	×	Suitable for a small number of indicators and objects, it cannot solve the problem of repeated evaluation information caused by the correlation between evaluation indicators.
AHP	[31], [32], [33], [34]	√	√	√	√	The judgment matrix is prone to serious inconsistency.
DEA	[32], [35], [36]	×	√	√	×	Multiple input-multiple output. It only indicates the relative development indicators of the evaluation unit, but cannot represent the actual development level.
EWM	[25], [38]	×	√	√	√	High data requirements. Unable to handle the correlation between weights.
FCE	[25]	√	×	×	√	Only the role of major factors is considered, while minor factors are ignored, making the evaluation results not comprehensive enough.
CRITIC	[30], [39]	×	√	√	×	Able to consider multiple criteria and quantify the importance of different criteria Requires a large amount of data and information.
VIKOR	[13], [31], [39], [40]	×	√	√	×	Sensitive to data quality and uncertainty. Affected by criteria weights and standardization methods.

effective and global decision-making method for energy assessment problems with complex factors. MCDM, as shown by Triantaphyllou [12], refers to the decision-making process of selecting from a set of limited or unlimited options that have conflicting and incommensurable criteria. Çelikbilek and Tüysüz [13] proposed a grey-based renewable energy assessment MCDM model using the decision-making trial and evaluation laboratory (DEMATEL), Analytic Network Process (ANP), and Multi-Criteria Optimization and Compromise Solution (MCOCS) methods, analyzing the efficiency of various forms of renewable energy. Vanegas-Cantarero et al. [14] proposed a multi-criteria evaluation framework including technical economics, environmental and social economics, and applied different case studies to a comprehensive overview, and can underpin medium and long-term decision-making and policy formulation. Liu et al. [15] proposed a sequential recursive method to evaluate the adjustability of distributed energy systems under three different initial states. Haralambopoulos and Polatidis [16] established a group decision-making framework for renewable energy projects based on the preference ranking organization method for enrichment evaluations II (PROMETHEE II) ranking method, aiming to achieve group consensus. Wang et al. [17] evaluated the economic performance of the proposed renewable energy-electricity-hydrogen system from the perspective of the whole life cycle, demonstrating the feasibility of hydrogen production using renewable energy. Li et al. [18] proposed a comprehensive weighting method of GRA-DEMATEL, analyzing the interrelationships between indicators to evaluate and select suitable renewable energy for cities. Liang et al. [19] adopted a method based on the Bayesian best-worst method (BBWM) and DQ-GRA technique to evaluate the comprehensive performance of 5G base station. Ozcan and Tuysuz [20] used the grey-DEMATEL method and an improved GRA method to evaluate the performance of retail stores. Derse [21] employed the unweighted GRA method and the GRA method based on DEMATEL to rank the alternative regions, and estimated the CO value of the region in the next period using the auto-regressive integrated moving average (ARIMA) method. Xue et al. [22] established a hybrid evaluation model based on DEMATEL-ANP and DQ-GRA techniques, which has good applicability to effectiveness evaluation of new and old kinetic energy conversion in Shandong Province from an electric power economics perspective. Zhao et al. [23] constructed a 3E performance evaluation index system for the CCHP-MG system, and designed a hybrid MCDM framework, involving integrated weighting method based on anti-entropy weight method and grey-DEMATEL, as well as the improved technique for order preference by similarity to ideal solution (TOPSIS) with DQGRA.

At present, the methods used in the literature on renewable energy evaluation are mostly entropy weight method (EWM), technique for order preference by similarity to ideal solution (TOPSIS), analytic hierarchy process (AHP), data envelopment analysis (DEA), etc. These methods, on one hand, neglect the correlation among indicators during the weighting process, and on the other hand, demand high data requirements. Table. 1 presents an analytical comparison of six methods: DEMATEL, GRA, TOPSIS, AHP, DEA, EWM, fuzzy comprehensive evaluation (FCE), criteria importance through intercriteria correlation (CRITIC), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR).

Therefore, under the background of energy transformation and technological evolution, this paper analyzes the characteristics and comprehensive benefits of renewable energy, and constructs an index system including economic benefits, environmental benefits, energy benefits and social benefits. On this basis, a hybrid MCDM model based on grey-DEMATEL and difference-quotient grey relational analysis (DQ-GRA) is established. Taking ten types of renewable energy in Fujian Province as the research object, the applicability and effectiveness of the proposed model are verified.

In summary, the main contributions of this study are as follows:

(1) By analyzing the development status of renewable energy, the comprehensive benefits evaluation index system of renewable energy is constructed, and the relationship between each index is studied by grey-DEMATEL, which provides a reference for the development of renewable energy.

(2) A hybrid MCDM model based on grey-DEMATEL and DQ-GRA method is established. Under the premise of enhancing reliability and reducing subjectivity, the correlation and causality between indicators are analyzed, which breaks through the limitations existing in traditional GRA that only takes the geometric similarity between data sequences into account and neglects the degree of numerical proximity. The proposed method has good applicability and effectiveness for the assessment issue in this paper.

The rest of the paper is organized as follows: Section II constructs the comprehensive benefit evaluation index system of renewable energy. Section III introduces the proposed hybrid MCDM model for the comprehensive benefits evaluation of renewable energy plans. In section IV, a case analysis is carried out using 10 renewable energy technology alternatives in Fujian Province, China. Finally, section V provides a conclusion.

II. COMPREHENSIVE BENEFITS EVALUATION SYSTEM OF RENEWABLE ENERGY PLANS

A. ESTABLISHMENT OF EVALUATION INDEX SYSTEM

Renewable energy will replace part of conventional power generation, especially thermal power generation using fossil fuels. Therefore, the development of renewable energy can decrease reliance on fossil fuels, thereby helping to strengthen national energy security, and can also reduce emissions of environmental pollutants. The accessibility and affordability of energy are crucial to a country's economic development and social stability. It could increase employment opportunities and government revenue, and contribute to the growth of the regional economy [27].

The comprehensive benefits of renewable energy cover multiple dimensions, which is a typical multi-criteria comprehensive evaluation problem. This paper builds on existing research work and uses relevant indicators suggested by the International Energy Agency (IEA) and references [31], [40]. The established index system is shown in Fig. 2. The applicable scope of this system is marked as follows.

B. INDICATOR DEFINITION

1) ECONOMIC BENEFITS (B_1)

Investment cost (C_1) is the overall investment in the implementation; increment in the GDP (C_2) is the increase in the contribution to Gross Domestic Product (GDP); operation and maintenance costs (C_3) is the maintenance and repair cost for the normal operation of the system equipment during the implementation process.

2) ENVIRONMENTAL BENEFITS (B_2)

Reduction in CO_2 emissions (C_4), reduction in SO_2 emissions (C_5), reduction in NO_X emissions (C_6) and reduction in particle emissions (C_7) are the cost savings of pollutant emissions caused by renewable energy replacing fossil energy power generation.

3) ENERGY BENEFITS (B_3)

Reduction in fossil energy (C_8) is the consumption of fossil energy reduced by renewable energy replacing fossil energy power generation.

4) SOCIAL BENEFITS (B_4)

Employment opportunity (C_9) indicates that the development of renewable energy creates new employment opportunities in a region. Social acceptance (C_{10}) indicates the public 's acceptance of it.

Among them, C_2, C_4, C_5, C_6, C_7, C_8, C_9 and C_{10} are benefit indicators, meaning the higher the value, the stronger the impact of the indicator. C_1 and C_3 are cost-type indicators, meaning the higher the value, the lower the impact of the indicator [41].

III. HYBRID MCDM METHOD

The evaluation will take into account the ten indicators mentioned above. The evaluation involves many aspects, and the relationship between different indicators is complicated. The paper proposes a hybrid MCDM method that combines grey theory, DEMATEL method, and DQ-GRA method. The detailed process is shown in Fig. 3.

A. EQUATIONS INDEX WEIGHT DETERMINATION METHOD BASED ON GREY-DEMATEL

DEMATEL is a method based on matrix or digraph analysis to examine the complex cause-and-effect relationships among system factors [42], [43]. This method can determine the priority of indicators in accordance with the type of relationship and the severity of its influence on other indicators. DEMATEL aims to establish a cause-and-effect

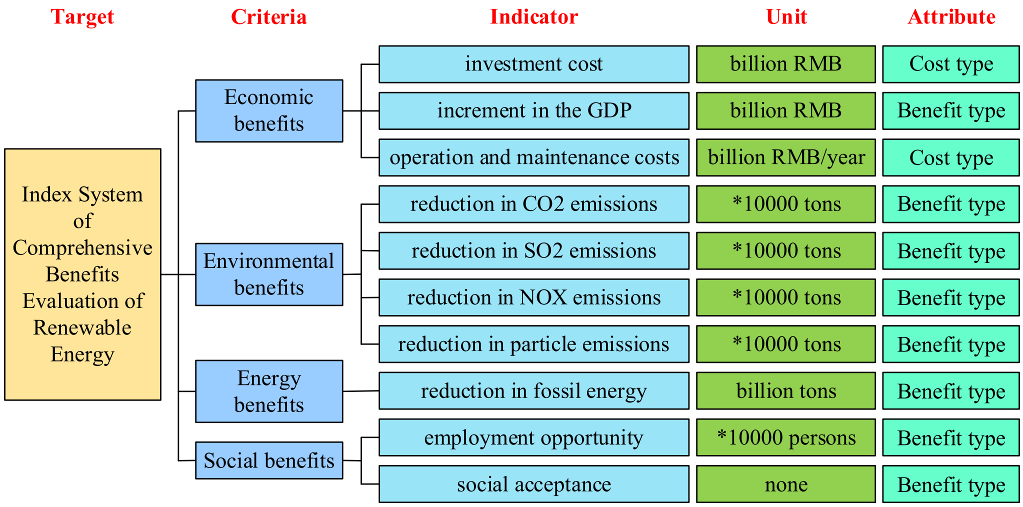

FIGURE 2. Comprehensive benefits evaluation index system. * The above evaluation index system is applicable to various renewable energy alternatives, including offshore wind power, onshore wind power, geothermal energy, solar water heating, large and medium-sized biogas, household biogas, biodiesel fuel, solar photovoltaic energy, biomass energy and tidal power.

diagram, obtain the cause degree and centrality of each indicator through matrix operation, and then clarify the role and the relationship between an indicator and other indicators. Although the classical DEMATEL is very effective in revealing the causal relationship between indicators and determining their priority, it grapples with challenges due to information deficit and uncertainty in judging the correlations among indicators, resulting in more subjective judgments. In order to overcome this and enhance its functionality, this paper adopts the grey system theory to modify the traditional DEMATEL. The grey system theory can address uncertainties in situations of data sparsity and incomplete information [44]. Its main benefit lies in producing satisfactory results with relatively limited data or in cases where factors exhibit significant variations [45]. Therefore, grey-DEMATEL can effectively avoid the uncertainty and fuzziness in the judgment process, thereby enhancing the accuracy of factor assessments. Specifically, this method can successfully partition complex factors into causal groups through causality diagrams, thereby facilitating the capture of problem complexity and enabling informed decision-making.

The calculation steps of the grey-DEMATEL used in this paper are as follows:

1) Establish the direct grey relation matrix.

TABLE 2. Linguistic scale and grey number representation.

Crisp value	Linguistic term	Grey number
4	Very High Influence (VH)	[0.75, 1]
3	High Influence (H)	[0.5, 0.75]
2	Low Influence (L)	[0.25, 0.5]
1	Very Low Influence (VL)	[0, 0.25]
0	No Influence (NI)	[0, 0]

Invite x experts in related fields to compare and score different indicators in pairs to obtain a direct impact matrix composed of semantic variables. Combining with the grey language scale in Table. 2 to assign expert semantic variables to grey numbers and the grey relation matrix $\otimes A^k = \left[\otimes a_{ij}^k\right]_{n\times n}$ is established. Finally, the total direct grey relation matrix A is calculated according to the experts' weights.

$$A^k = \begin{bmatrix} 0 & \otimes a_{12}^k & \cdots & \otimes a_{1n}^k \\ \otimes a_{21}^k & 0 & \cdots & \otimes a_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \otimes a_{n1}^k & \otimes a_{n2}^k & \cdots & 0 \end{bmatrix} \tag{1}$$

where n denotes the quantity of indicators, $\otimes a_{ij}^k$ is the element in the grey relation matrix, which is the evaluation value of the kth expert on the direct influence of indicator i on indicator j. Obviously, $\otimes a_{ij}^k$ is a grey number, denoted by $\otimes a_{ij}^k = \left[\underline{\otimes} a_{ij}^k, \bar{\otimes} a_{ij}^k\right]$, $\underline{\otimes} a_{ij}^k$ and $\bar{\otimes} a_{ij}^k$ are the lower and upper limits of $\otimes a_{ij}^k$. According to Lin [46], it sets $\otimes a_{ii}^k = [0, 0]$.

2) Compute the crisp relation matrix

Using the modified Converting Fuzzy Data into Crisp Scores (CFCS) method [47], [48] converted the grey value into crisp values, and obtained the clarity direct influence matrix. The method is divided into the following three steps:

(i) Normalization of the grey value.

$$\begin{aligned} \underline{\otimes} b_{ij}^k &= \left(\underline{\otimes} a_{ij}^k - \min_j \underline{\otimes} a_{ij}^k\right) / \Delta_{\min}^{\max} \\ \overline{\otimes} b_{ij}^k &= \left(\overline{\otimes} a_{ij}^k - \min_j \overline{\otimes} a_{ij}^k\right) / \Delta_{\min}^{\max} \\ \Delta_{\min}^{\max} &= \max_j \overline{\otimes} a_{ij}^k - \min_j \underline{\otimes} a_{ij}^k \end{aligned} \tag{2}$$

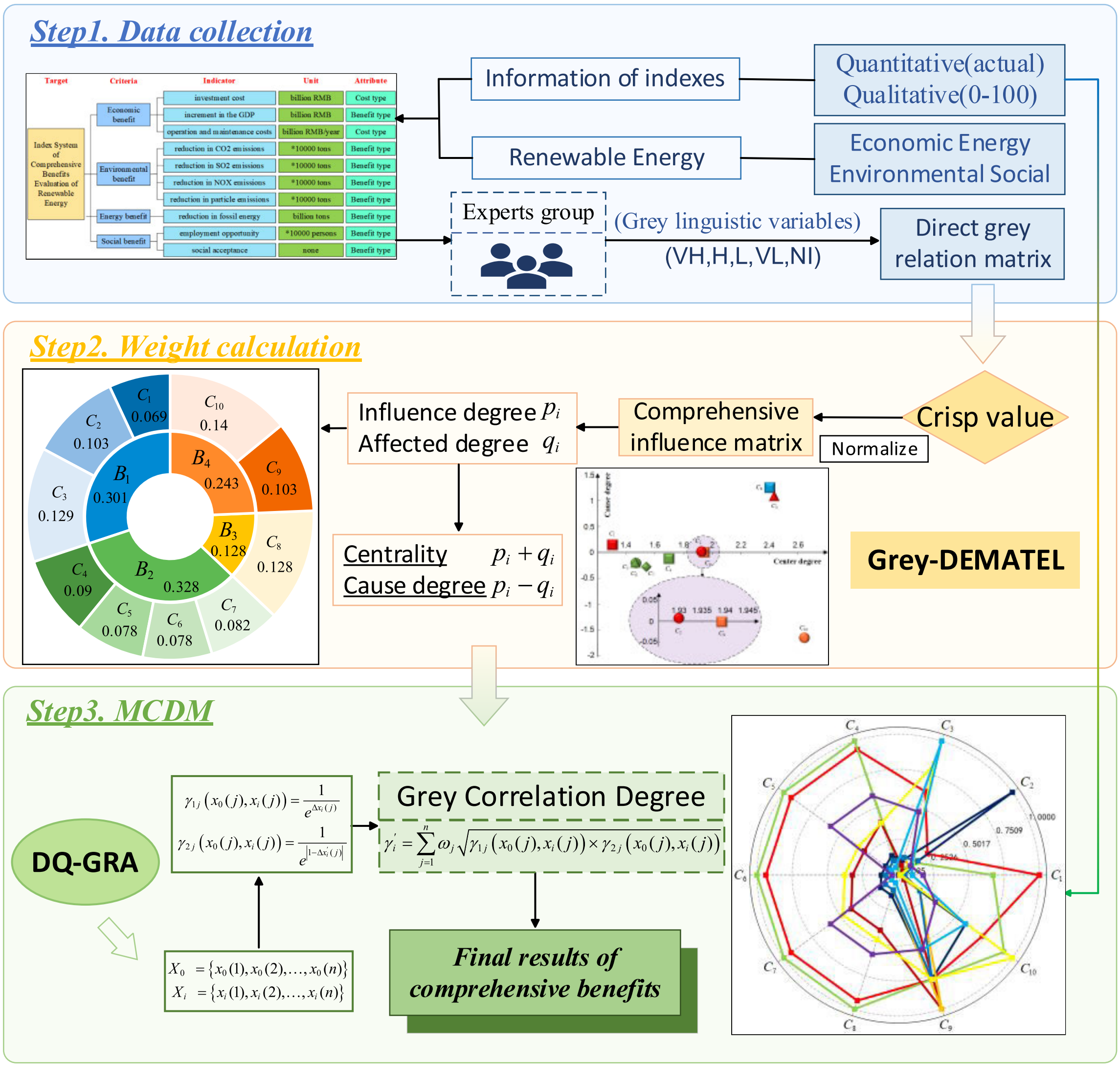

FIGURE 3. Framework of the proposed hybrid MCDM model.

where $\underline{\otimes} b_{ij}^{k}$ and $\overline{\otimes} b_{ij}^{k}$ are the lower and upper limits of $\otimes a_{ij}^{k}$ after the clarification.

(ii) Computing total normalized crisp value.

$$B_{ij}^{k} = \frac{\underline{\otimes} b_{ij}^{k}\left(1 - \underline{\otimes} b_{ij}^{k}\right) + \overline{\otimes} b_{ij}^{k} \times \overline{\otimes} b_{ij}^{k}}{1 - \underline{\otimes} b_{ij}^{k} + \overline{\otimes} b_{ij}^{k}} \tag{3}$$

(iii) Calculating the final crisp values.

$$C_{ij}^{k} = \min \underline{\otimes} a_{ij}^{k} + B_{ij}^{k} \Delta_{\min}^{\max} \tag{4}$$

3) Calculate the real numbered direct influence matrix. Combining all the $C^{k} = \left[c_{ij}^{k}\right]_{n\times n}$, gives:

$$C = \sum_{k=1}^{f} c_{ij}^{k}/k \tag{5}$$

4) Determine the comprehensive influence matrix.

The input data of $C^{k} = \left[c_{ij}^{k}\right]_{n\times n}$ are normalized by Equation (6) to obtain the normalized direct relation matrix S. The specific processing method adopts the 'maximum value method', i.e., the current value of the matrix is divided by the maximum value of the 'direct influence matrix'. The comprehensive influence matrix $X = \left[x_{ij}\right]_{n\times n}$ is calculated by (7).

$$S = c/\max_{1\le i\le n} \sum_{j=1}^{n} c_{ij} \tag{6}$$

$$X = S + S^2 + S^3 + \cdots = \sum_{i=1}^{\infty} S^i = S(I-S)^{-1} \tag{7}$$

where I refers to the unit matrix.

5) Calculate the center degree and the cause degree.

According to (8)-(9), the influence degree p_i and the affected degree q_i are calculated, and the centrality M_i and the cause degree N_i are calculated according to (10) and (11).

$$p_i = \left[\sum_{j=1}^{n} x_{ij}\right]_{n\times 1} \tag{8}$$

$$q_i = \left[\sum_{i=1}^{n} x_{ii}\right]_{n\times 1} \tag{9}$$

$$M_i = p_i + q_i \tag{10}$$

$$N_i = p_i - q_i \tag{11}$$

where p_i and q_i represent the sum of the ith row elements and the sum of the jth column elements in the comprehensive influence matrix X, respectively.

M_i reflects its position and importance within the index system. The larger the centrality, the greater the importance of the indicator in the system. N_i reflects the net impact of the indicator on the system. $N_i > 0$ shows that the impact of this indicator on other indicators is larger than the impact of other indicators on it, which is called the cause indicator; $N_i < 0$ shows that the impact of the indicator on other indicators is less than the impact of other indicators on it, and the index is called the result index; $N_i = 0$ means equal, and the indicator may be eliminated.

6) Determine the index weight.

Based on the centrality, each indicator's weight is:

$$\omega_i = M_i / \sum_i M_i \tag{12}$$

where ω_i is the weight of indicator i.

B. COMPREHENSIVE EVALUATION METHOD BASED ON DQ-GRA

GRA is an important analysis method based on the grey system theory proposed by Deng Julong in 1982 [44], which is mainly applied to study the correlation between indicators in a system, especially in the case of limited sample data or incomplete information. However, the traditional GRA mainly focuses on the geometric similarity between data sequences, but ignores the numerical proximity. The two curves are parallel, and according to traditional GRA calculation, the grey relational degree is determined as 1. However, in reality, these two curves are not perfectly aligned. As a result, there is a bias in the calculation, which can lead to inaccurate analysis.

To address this limitation, an improved method of DQ-GRA is proposed [49]. This method incorporates the difference method and the division method, and considers the geometric similarity and numerical proximity between the data sequences. In the DQ-GRA method, the core concept is to assess the similarity between two sequences. Specifically, when the difference of the data points in two sequences is gradually approaching 0, or the quotient value is gradually approaching 1, it means that the grey relationship values between these two sequences are closer, thus indicating a higher degree of similarity between them [22]. This modified DQ-GRA method can not only evaluate the correlation between data sequences more comprehensively, but also reduce the subjectivity and enhance the accuracy and reliability in the calculation process.

The calculation steps of DQ-GRA used in this study are as follows:

1) Determine the reference sequence X_0 and comparison sequence X_i.

X_0 is composed of standard optimal values or target values. The optimal value of the benefit index takes the maximum value, and the optimal value of the cost index takes the minimum value.

$$X_0 = \{x_0(1), x_0(2), \ldots, x_0(n)\} \tag{13}$$

$$X_i = \{x_i(1), x_i(2), \ldots, x_i(n)\} \tag{14}$$

where, $x_0\,(j)$ is the optimal value of the jth indicator; $x_i\,(j)$ is the ith indicator value of the jth scheme.

2) Data normalization to obtain dimensionless and consistent sequences.

For X_0, the normalized sequence is $X_0 = \{1, 1, \ldots, 1\}$. For X_i to be evaluated, obtain the normalized sequence $X_i' = \left\{x_i'(1), x_i'(2), \ldots, x_i'(n)\right\}$ based on the index attribute. Normalize the benefit index:

$$x_i'(j) = \frac{x_i(j)}{x_0(j)} \tag{15}$$

For cost-based indicators, the normalized values are as follows:

$$x_i'(j) = \frac{x_0(j)}{x_i(j)} \tag{16}$$

3) Calculate the difference matrix.

The difference between the components of X_0 and X_i is calculated, and the difference matrix is formed, as shown in (17).

$$\Delta x_i(j) = \left|x_0'(j) - x_i'(j)\right| \tag{17}$$

where $\Delta x_i(j)$ is the difference between the jth index value of X_i and the jth index value of the ith scheme in X_0.

$\Delta x_i(j)$ is introduced into the following formula to form the grey correlation degree $\gamma_{1j}\,(x_0(j), x_i(j))$ of geometric similarity.

$$\gamma_{1j}\,(x_0(j), x_i(j)) = \frac{1}{e^{\Delta x_i(j)}} \tag{18}$$

4) Compute quotient matrix.

Find the quotient of each component of X_0 and X_i to compose a quotient matrix:

$$\Delta x_i^{\cdot}(j) = \frac{x_i'(j)}{x_0'(j)} \tag{19}$$

where $\Delta x_i^{\cdot}(j)$ is the quotient of the jth index value of X_i and the jth index value of the ith scheme of X_0.

$\Delta x_i^{\cdot}(j)$ is introduced into the following formula to form the grey correlation degree $\gamma_{2j}\,(x_0(j), x_i(j))$ of numerical proximity.

$$\gamma_{2j}\,(x_0(j), x_i(j)) = \frac{1}{e^{\left|1-\Delta x_i^{\cdot}(j)\right|}} \tag{20}$$

5) Calculate the comprehensive grey correlation degree. The γ_i' between X_i and X_0 of each scheme is obtained.

$$\gamma_i' = \sum_{j=1}^{n} \omega_j \sqrt{\gamma_{1j}\left(x_0(j), x_i(j)\right) \times \gamma_{2j}\left(x_0(j), x_i(j)\right)} \tag{21}$$

Among them, ω_j is the weight of the jth index calculated by grey-DEMATEL.

C. APPLICABILITY OF THE PROPOSED METHOD

The method proposed in this paper consists of two main parts: one part is according to grey-DEMATEL to weight the indicators, and the other part is according to DQ-GRA to sort the evaluation plans.

1) APPLICABILITY OF INDICATOR WEIGHTING METHOD

The quantitative indicator in the index system of this paper can directly obtain the corresponding indicator data. However, for the qualitative indicators (such as social acceptance), due to the ambiguity and uncertainty of the indicator, it is impossible to directly obtain its specific value. Although the objective weighting method can assign weights to quantitative indicators and reduce the subjectivity of assessments, objective weights will also change accordingly as the evaluation objects change, with poor stability. It fails to show the significance of the indicator itself and has weak explanatory power.

In this paper's evaluation system, there is a relevance among the indicators. The significance of the indicators mainly relies on their rank within the system, that the interactive relationship with others. So DEMATEL serves as an effective method to reveal the interaction of each indicator in complex systems and determine the priority of each indicator, exhibiting good applicability for weight determination in this study. But the classical DEMATEL grapples with challenges due to information deficit and uncertainty, resulting in more subjective judgments. In order to overcome this and enhance its functionality, this paper introduces the grey system theory to modify the traditional DEMATEL. This method not only addresses uncertainty and fuzziness in the analysis, but also reduces subjectivity and takes into account the correlation between indicators, so as to ensure a sound analysis [23].

2) THE APPLICABILITY AND ADVANTAGES OF MCDM METHOD

In gray system theory, GRA is used as an analytical method whose core concept is to assess the degree of association between data series based on their similarity [24], [50]. Although the traditional GRA method considers the absolute value of the difference from two data series, i.e., the geometric similarity, when calculating the degree of association, it neglects the importance of numerical proximity. To solve this problem, this paper proposes an innovative GRA method, which integrates the difference and division methods to define the integrated grey correlation in terms of both geometric and numerical similarity, thus overcoming the restriction of the traditional methods. In addition, the optimized GRA method eliminates the tediousness of setting resolution coefficients, which further reduces the subjectivity. This method improves the accuracy and objectivity of GRA.

The improvement of GRA not only retains the strengths of the original method in handling small samples and incomplete information problems, but also overcomes its limitations by considering numerical proximity, making it a more comprehensive and accurate analysis tool. This improvement increases the dimension of analysis and improves the applicability and accuracy in multivariate complex system analysis. Therefore, DQ-GRA is considered to be a more effective analysis tool in dealing with small samples and incomplete information problems. Moreover, the application of the DQ-GRA in MCDM problems also shows its wide applicability and effectiveness.

IV. RESULTS

A. BASIC INFORMATION OF THE CASE

In this paper, the proposed methodology is validated using actual data from a renewable energy technology alternative program in Fujian Province, China to ensure its feasibility [35], [40]. The province has 10 renewable energy alternatives to be developed: offshore wind power (S_1), onshore wind power (S_2), geothermal energy (S_3), solar water heating (S_4), large and medium-sized biogas (S_5), household biogas (S_6), biodiesel fuel (S_7), solar photovoltaic energy (S_8), biomass energy (S_9) and tidal power (S_{10}). The evaluation indicator data of each scheme are shown in Table. 3.

According to Table. 3, the performance of different indicators for each scheme is calculated. Fig. 4 and Fig. 5 below are the performance of 10 renewable energy technology alternatives in C_1-C_{10} and B_1-B_4 respectively.

It can be seen from Fig. 4 that the investment cost (C_1) of solar water heating (S_4) is the lowest; the increment in the GDP (C_2) of solar water heating (S_4) is the highest; onshore wind power (S_2) has the lowest operation and maintenance costs (C_3); onshore wind power (S_2) has the highest reduction in CO_2 emissions(C_4), reduction in SO_2 emissions(C_5), reduction in NO_X emissions(C_6), reduction in particle emissions(C_7) and reduction in fossil energy(C_8); large and medium-sized biogas (S_5) has the highest employment opportunity (C_9); biodiesel fuel (S_7) has the highest social acceptance (C_{10}).

It can be seen from Fig. 5: In terms of economic benefits, S_1 has the best performance, followed by S_8. In terms of environmental benefits and energy benefits, S_2 has the best performance and S_1 ranks second. In terms of social benefits, S_7 is the best, followed by S_2 and S_1.

B. INDEX WEIGHTING RESULTS

This paper invites four experts in related fields to construct a semantic direct impact matrix through a pairwise comparison method, assuming that each expert 's evaluation weight value is consistent. Combined with Table 1, it is converted into a

TABLE 3. Evaluation indicator value.

Indicator	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
S_1	353.1	1455.33	0.33	427.33	35412.3	30429	14773.5	153.91	0.7	0.7
S_2	237.25	849.66	0.02	456.4	37821.3	32499	15778.5	164.38	0.7	0.88
S_3	13.71	247.67	0.04	179.38	11127.11	10520.17	6473.95	67.44	0.9	0.05
S_4	1.23	5644.72	0.06	66.17	4104.38	3880.5	2388	24.88	0.7	0.56
S_5	4.32	551.73	0.07	49.34	3060.7	2893.76	1780.77	18.55	0.9	0.18
S_6	16.2	979.4	0.07	48.43	3004.16	2840.29	1747.87	18.21	0.7	0.18
S_7	7.5	716	0.44	177.6	13058.6	12346.31	7597.73	79.14	0.7	0.95
S_8	35.59	670.1	0.53	26.11	2164.09	1380	902.83	9.41	0.5	0.56
S_9	62.48	608.18	0.25	269.51	22333.84	1380	9317.36	97.07	0.5	0.31
S_{10}	66.6	551.73	0.47	99.81	8270.09	1380	3450.5	4.54	0.5	0.05

grey relation matrix. The data for each indicator are obtained from (2)-(11). as shown in Table. 4.

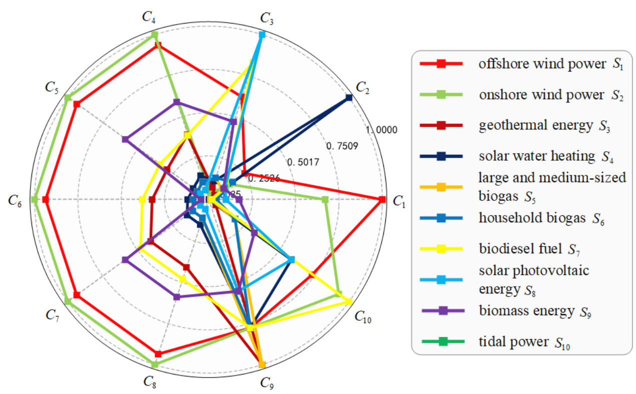

FIGURE 4. Performance in ten indicators.

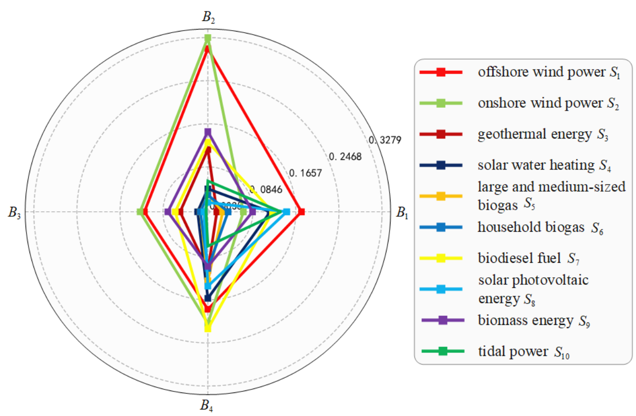

FIGURE 5. Performance in four dimensions.

Analysis of cause degree: cause indicator is the core indicator of comprehensive benefits evaluation. The greater the degree of cause N (greater than 0), the greater the impact on other indicators. There are four cause indicators: $C_8 > C_3 > C_1 > C_2$. Among them, C_8 reduction in fossil energy is the primary cause index. In the comprehensive benefit evaluation, it is basically not disturbed by others, but it has the greatest impact, followed by C_3 operation and maintenance costs, and C_1 investment costs. It can be seen that these three indicators are relatively stable, and the energy consumption benefits and economic costs of renewable energy technology alternatives are relatively stable, and need to be gradually improved according to different scenarios. Therefore, these cause indicators are the root cause of improving the comprehensive benefits.

TABLE 4. Data of indicators.

Indicator	p	q	M	N
C_1	0.7298	0.7298	1.3040	0.1556
C_2	0.9685	0.9685	1.9299	0.0071
C_3	1.7524	1.7524	2.4320	1.0729
C_4	0.7873	0.7873	1.6988	-0.1242
C_5	0.6281	0.6281	1.4671	-0.2110
C_6	0.6281	0.6281	1.4671	-0.2110
C_7	0.6281	0.6281	1.5396	-0.2834
C_8	1.8303	1.8303	2.4044	1.2561
C_9	0.9685	0.9685	1.9393	-0.0023
C_{10}	0.4908	0.4908	2.6416	-1.6599

Result analysis: the result indicator is the direct indicator of comprehensive benefit evaluation. The greater the result degree N (less than 0), the greater the influence of other indicators. From the table, it can be seen that there are 6 results indicators: $C_9 > C_4 > C_{10} > (C_5, C_5) > C_7$. Among them, the C_9 is the most direct impact on the comprehensive benefit index, followed by the C_4, and the C_{10}. It can be seen that the short-term adjustment of these indicators has a significant impact on comprehensive benefits, especially employment opportunities. However, these indicators are often short-term, stimulating but not sustained, and are not an effective means to fundamentally improve efficiency. The result index can be used as a short-term strategy for program improvement, but

TABLE 5. Results of comprehensive evaluation.

Plan	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
γ'	0.6667	0.8415	0.4879	0.5572	0.4089	0.3857	0.5222	0.3787	0.4603	0.3547

it still needs to be considered in combination with the cause index and the central index.

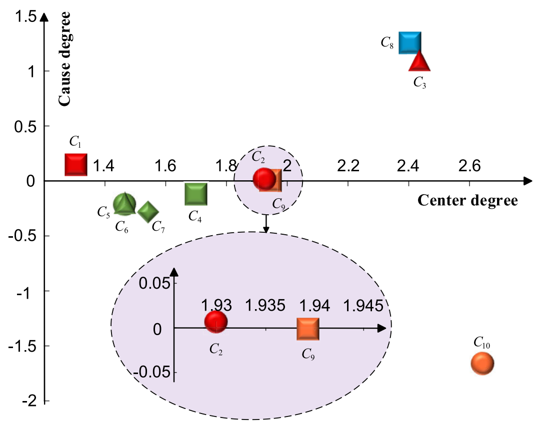

FIGURE 6. Cause-effect relation diagram.

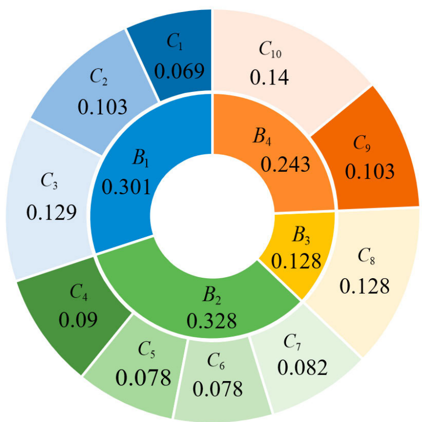

FIGURE 7. The weight of evaluation index.

Centrality analysis: Centrality M indicates the correlation between indicators and other indicators. The larger the centrality value is, the greater the correlation influence on the comprehensive benefit is. This indicator should be paid more attention to in the improvement of comprehensive benefit. Sorted according to the size of the centrality: $C_{10} > C_3 > C_8 > C_9 > C_2 > C_4 > C_7 > C_5 > C_6 > C_1$. It can be seen that C_{10}, C_3, and C_8 are key indicators for comprehensive benefit assessment, which is also the difference between renewable energy and traditional energy.

The calculation results of the cause degree and centrality of all indicators in Table. 4 are plotted to draw a centrality-cause degree scatter plot, as shown in Fig. 6.

TABLE 6. Comparison results of different evaluation methods.

Evaluation methods	Ranking results
Grey-DEMATEL and DQ-GRA	$S_2 > S_1 > S_4 > S_7 > S_3 > S_9 > S_5 > S_6 > S_8 > S_{10}$
Entropy weight method	$S_2 > S_1 > S_7 > S_4 > S_3 > S_9 > S_5 > S_6 > S_8 > S_{10}$

Thus, the weight of each indicator is obtained, as shown in Fig. 7.

C. COMPREHENSIVE BENEFITS EVALUATION RESULTS

Based on the indicator weights determined by grey-DEMATEL, DQ-GRA is used to comprehensively evaluate 10 renewable energy plans. The evaluation results of each plan are shown in Table. 5.

The renewable energy technology plan is ranked on the basis of a composite gray correlation, where the better the value, the more well performed the technology solution is. Rank the programs as $S_2 > S_1 > S_4 > S_7 > S_3 > S_9 > S_5 > S_6 > S_8 > S_{10}$ in descending order. It shows that S_2 has the highest relative comprehensive benefit among the ten schemes, i.e., the scheme is relatively optimal, followed by S_1. It can be seen that the province should prioritize S_2 in the selection of options. If S_2 is not available for any reason, S_1 can be taking into account.

D. COMPARATIVE ANALYSIS OF DIFFERENT METHODS

To validate the accuracy of the proposed method, select the entropy weight method [51] make a comparison. The results are shown in Table. 6.

The evaluation results of the two methods are basically consistent, indicating that this method is effective. Unlike the entropy weight method, the grey-DEMATEL and modified DQ-GRA can be weighted on the basis of considering the correlation between indicators, which can provide data support and reference for the development and application of renewable energy.

V. CONCLUSION

Renewable energy matters in the world energy transition. How to evaluate the comprehensive benefits of renewable energy plans contributes to the development of renewable energy. Based on the comprehensive benefits of renewable energy plans, this paper proposes a MCDM evaluation method based on grey-DEMATEL and DQGRA. The main conclusions are summarized as follows:

1) In this paper, the grey-DEMATEL method is used to determine the indicator weights, and the traditional DEMATEL method is optimized by combining the grey system theory in order to reduce the subjectivity and fully take into account the indicators' correlation, so as to ensure the reliability of the weighted results.

2) The modified DQ-GRA method proposed in this paper not only eliminates the tediousness of setting resolution coefficients, but also defines the integrated grey correlation in terms of both geometric and numerical similarity. This new method effectively breaks through the limitations existing in the traditional grey correlation degree, and has good applicability to the evaluation of multi-objective and multi-criteria models.

Due to data accessibility, the final evaluation results may be affected to some extent. In the future, we will further expand the scope of research, and based on comprehensive benefit evaluation, further analyze the operational risks in renewable energy generation process to improve the comprehensive evaluation of renewable energy generation technology.

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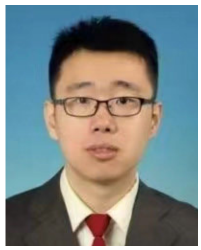

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