Evaluating the Comprehensive Perception of Green Development Potential in Regional Power Grids: An Analysis of Socio-Physical Attributes

Yi Zhang, Wei Rao*, Wei Hu

Abstract—**Quantitatively assessing the green development potential of power grids is crucial for planning low-carbon development paths for regional grids. In this paper, we focus on the distance measure and score function of Probability Interval-Valued Hesitant Fuzzy Set （PIVHFs）, and then propose an improved TOIDM framework based on distance-shaped entropy measure to assess this potential. Initially, we construct a comprehensive evaluation framework encompassing energy, economic, and social dimensions. Subsequently, we develop a novel score function and a new distance measure. The novel distance measure integrates both fuzzy and interval uncertainty variations, offering a more generalized approach to uncertainty quantification. Furthermore, a weighting model is constructed based on the Distance-type entropy measure. We then propose an improved TODIM method for probabilistic interval hesitant fuzzy environments. Eventually, we applied the proposed framework to assess the low-carbon development potential of regional power grids in Shanghai. Through comprehensive sensitivity analysis and actual conditions, the results validate the theoretical robustness and practical effectiveness of this approach.**

Index Terms—**potential perceive, probabilistic interval-valued hesitant fuzzy set, fuzzy entropy, distance measure, improved TODIM, low carbon grid**

I. Introduction

In recent years, The growing severity of energy scarcity and environmental degradation in China has drawn significant academic and policy attention to the development of a low-carbon energy system. In this context, regional grids (RGs) must explore innovative pathways for green development (GD). The GD potential of RGs reflects their current efforts in the low-carbon sector. Consequently, Quantitative assessment of this potential is crucial for tailoring effective low-carbon development strategies for regional power grids [1].

In the field of power system evaluation, existing research primarily concentrates on low-carbon power systems and low-carbon grids. At low-carbon power system aspect, Li et al [2]. utilized the affiliation function to develop a low-carbon evaluation system for the power system, encompassing ‘source-network-load’. This framework provides a theoretical foundation for assessing the low-carbon level of urban power systems. Wu et al. [3] concentrated on the characteristics of renewable energy, integrating time-series operation simulations of the power system with energy-saving economic evaluation methods. This approach enabled an in-depth analysis of the energy-saving and low-carbon aspects of the Southern Power Grid (SPG). In the context of green power grids, Li et al. [4] explored the pathways for RGs to achieve green development. They developed a low-carbon benefit evaluation model for grids and investigated the development trends in the low-carbon benefits of these grids. Building on this foundation. Sun et al [5]. incorporated the entire life cycle of power grid engineering and proposed a comprehensive green power grid evaluation index system. This system encompasses aspects of grid planning, construction, operation, and equipment. They applied this index system to evaluate grid samples from several cities in Shandong Province, thereby elucidating sustainable progress within the regional power grid. In addition to comprehensive evaluations spanning multiple dimensions, some studies also emphasize specific aspects of the sustainable evolution of power grids. Du et al [6]. focused on evaluating the carbon neutrality capability of power grids. Applying the RF-MARCOS method, they assessed the carbon neutrality potential of urban power grids in Shanxi. Xiang et al [7]. concentrated on the operation of distribution grids, developing a comprehensive assessment framework from the perspective of low-carbon technologies. This system comprehensively reflects the contributions of distribution grids in areas such as low-carbon power supply and low-loss flexibility.

The review of current literature indicates that research on RGs’ low-carbon transformation potential remains insufficient. Simultaneously, most of the research is based on the physical attributes of power grids, focusing on the selection of indicators related to energy as well as low-carbon technologies. In addition, current studies have largely overlooked the human and social factors associated with RGs. Given the intricate interdependence between the energy system and the social system [8], it is imperative to incorporate the impact of social factors in the study of power grids.

Given the practicality of numerical decision-making

Manuscript received March 2, 2024; revised March 5, 2025.

Yi Zhang is a professor of the School of Economics and Management, Shanghai University of Electric Power, Shanghai 200090, China (e-mail: zhangyishxy@163.com).

Wei Rao is a postgraduate student of the School of Economics and Management, Shanghai University of Electric Power, Shanghai 200090, China (Corresponding author, phone: +8618770160280; e-mail: raowei2023@163.com).

Wei Hu is a professor of the School of Economics and Management, Shanghai University of Electric Power, Shanghai 200090, China (e-mail: hwshiep@shiep.edu.cn).

frameworks, existing evaluation studies related to low-carbon development employ the analytic hierarchy process (AHP) [9], and fuzzy comprehensive evaluation methods [6]-[7]. However, these traditional methods often lack consideration of ambiguity and uncertainty [10]. Moreover, these methods tend to overlook psychological factors that may influence decision-makers' judgments regarding the degree of elemental affiliation [11], potentially affecting the rationality and accuracy of the evaluations.

Evaluating low-carbon power grids involves diverse indicators and significant uncertainty. This requires systematic processing of decision-making information. Developing comprehensive evaluation frameworks is essential for accurate assessment. The hesitant fuzzy set, proposed by Torra [12] as an extension of the fuzzy set, permits multiple degrees of membership to capture decision-making information. This approach enhances alignment between the decision-making process and real-world scenarios. Building on this, Zhang et al [13]. and Zhou et al [14]. introduced probability and interval values into the hesitant fuzzy sets, forming probabilistic interval-valued hesitant fuzzy set (PIVHFs). PIVHFs utilizes affiliation intervals and probabilities to represent decision-making information. It accounts for the decision-maker's hesitation psychology and significantly reduces information gaps in the decision-making process.

Building upon the preceding analysis, this study integrates the socio-physical attributes of power grids to develop an evaluation framework for assessing the GDP of RGs. Subsequently, we proposed an analytical decision-making framework based on a PIVHF environment. Within this framework, the distance measure and scoring function of PIVHFs are enhanced and applied to the TODIM method. An improved entropy weight method based on fuzzy entropy measurement will be employed to calculate the criteria weights. Finally, the practicality and rationality of the proposed method are validated through an assessment of the GD potential of the power grid in Shanghai's newly urbanized areas.

II. Indicator System For Assessment Of Green Development Potential Of Regional Power Grids

In this section, we constructed a multidimensional assessment system for evaluating the GD potential of RGs, based on criteria from the energy-material, economy-technology, and humanity-society dimensions. With the integration of new energy sources and the transition from unidirectional to bidirectional power flow, the grid is increasingly influenced by social attributes compared to the power generation sector [15]. However, existing studies for power grids predominantly mainly focus on the physical attributes of energy, often neglecting human and social factors. This paper addresses this gap by incorporating carbon emissions from RGs across their entire life cycle (spanning planning, operation, and maintenance) based on low-carbon power grid assessment indicators.

A. Energy-physical criteria

Energy-physical attributes are the fundamental characteristics of power grids as electricity transmission carriers. In the context of policies promoting renewable energy integration, achieving the GD of RGs demands high standards for their performance in renewable energy integration [16]. Considering the driving factors behind green development, the selection of energy-physics indicators emphasizes both clean energy generation and energy utilization efficiency, as outlined below:

1) Installed share of distributed power supply (C_1): Distributed power supply constitutes a crucial component of the new power system, characterized by its cleanliness and flexibility. This type of power supply can effectively meet regional power demand while promoting the GD of RGs.

2) Reasonableness of regional power grid capacity-load ratio (C_2): The capacity-load ratio serves as a critical indicator of power supply adequacy in regional grids, providing essential insights for optimizing grid planning and infrastructure development to maintain reliable electricity supply. An excessively high capacity-load ratio results in resource waste, while an excessively low ratio leads to insufficient regional power supply and reduced grid resilience [17]. A reasonable capacity-load ratio can effectively enhance the resource allocation efficiency of the regional power grid and reduce carbon emissions.

3) Renewable energy consumption rate (C_3): The renewable energy consumption rate reflects the energy utilization efficiency of the regional power grid. Higher energy utilization efficiency corresponds to lower carbon emissions and a greater potential for low-carbon development.

4) Electricity as a percentage of final energy consumption (C_4): Electricity is cleaner and more efficient than traditional fossil fuels [18]. Using electricity to replace traditional fossil energy facilitates centralized energy control and promotes regional low-carbon development.

5) Grid energy consumption (C_5): To maintain the safe and reliable operation of the RG, management protocols and regular maintenance procedures must be implemented. Maintenance and management tasks encompass energy-consuming activities such as manual inspections and power supply operations for office buildings, which result in carbon dioxide emissions. The energy consumption level of the grid itself reflects the efficiency of the regional grid in managing carbon emissions at the operations and maintenance (O&M) level. Higher management efficiency indicates a greater potential for green development in the region.

B. Economic-technical criteria

The sustainable evolution of power grid needs both financial and technical support [19]. Combined with the development trend of grid intelligence, this paper selects corresponding indicators from the perspective of the economy and intelligence level.

1) Expectation of regional grid investment growth (C_6): Low-carbon development requires financial support, and the economic status of grid companies is directly related to their low-carbon development potential.

2) Operation and maintenance efficiency (C_7): With the advancement of technology, drones, artificial intelligence, and other innovations have been widely adopted in grid maintenance. The adoption of these technologies over traditional manual maintenance can significantly reduce

carbon emissions and decrease maintenance costs.

3) Intelligent degree of regional power grid (C_8): The smart grid seamlessly integrates all aspects of grid operations, enabling reliable and low-carbon performance. The level of smart grid intelligence is closely tied to grid operational efficiency and reflects the advancement of low-carbon technologies in regional power grids.

4) Regional grid loss management (C_9): This criterion represents the proportion of power loss occurring during the transmission and distribution processes relative to the total amount of power connected to the grid. Transmission losses, as a major source of carbon emissions in power grids, reflect the low-carbon technological advancement of regional power grids. Consequently, it is a critical factor in assessing the low-carbon development of RGs.

5) Grid safety operation level (C_{10}): During the long-term operation of regional power grids, equipment failures or damage may occur due to aging infrastructure, improper operation, and other issues. Timely detection of aging and faulty equipment, along with rapid repair or replacement, is the primary goal of maintenance management. It is also a necessary requirement for ensuring the security and low-carbon development of RGs.

C. Human-social criteria

The social attributes of RGs are mainly reflected in the interactions with users outside the enterprise, the government, and employees inside the enterprise during the life cycle of grid operation [9]. We integrate social structure and refine the human-social criteria for assessing the GD potential of RGs, focusing on three levels: users, government, and enterprises.

1) Quality of carbon information disclosure of power grid enterprises (C_{11}): Carbon information of listed companies includes financial and non-financial statements of greenhouse gases disclosed by the enterprises. The extent of such disclosures reflects the priority regional power grid enterprises give to carbon emission management and highlights their efforts in reducing carbon emissions.

2) Local policy preferences (C_{12}): This criterion specifically refers to the intensity of locally relevant carbon emission incentive policies. Incentive-based emission reduction policies can promote the development of a regional green economy.

3) Regional Grid Green Innovation Capacity (C_{13}): The innovation capacity of the regional grid can be measured by the quantity of disclosed utility model patents related to carbon emission reduction technologies. The level of technological innovation is closely linked to energy use and regulation [20]. A high level of green innovation capability contributes to the GD of the grid.

4) Load Response Situation (C_{14}): Demand response is an important tool for grid load regulation, peak shaving, and valley filling. The willingness of regional residents to participate in demand response programs can significantly impact the comprehensive operational efficiency and system performance of the RG infrastructure. Consequently, assessing the load response willingness of residents is a crucial aspect of evaluating sustainable development potential of the power grid.

5) Acceptance of new technology (C_{15}): High acceptance of new technology among employees indicates their ability to adapt to new O&M models and embrace new working methods. This acceptance is crucial for promoting the intelligence of regional power grid O&M and enhancing overall efficiency.

III. COMPREHENSIVE ASSESSMENT MODEL FOR GREEN DEVELOPMENT OF REGIONAL POWER GRIDS

Given the subjective factors inherent in the social attributes of regional power grids, this paper uses PIVHFEs to represent assessment information, ensuring a comprehensive decision-making process. The comprehensive assessment model for the GD potential of regional power grids under a PIVHF environment is constructed as follows:

1) Information Conversion: the model first utilizes the utility function to convert various forms of information, such as data and semantic evaluations, into PIVHF numbers.

2) Weight Determination: the model combines PIVHF entropy with an improved entropy weighting method to determine the weights of each criterion.

3) Comprehensive Assessment: the model establishes an interactive multi-criteria decision-making approach within a PIVHF framework assess the green development potential of RGs comprehensively.

A. The new distance measure and score function

This section aims to improve the limitations of current PIVHF distance measurement and scoring mechanisms. Through the application of probability hesitant fuzzy set theory [21]-[22], we establish enhanced methods for PIVHF distance measure and scoring function, consequently advancing decision-making accuracy.

Zhou et al [14]. introduced interval values into probabilistic hesitant fuzzy sets in 2019. They defined PIVHFs and proposed a correlation operator for these sets. In PIVHFs, the form of affiliation is replaced by affiliation intervals instead of exact values. Compared to other hesitant fuzzy sets, this interval-based representation provides a more precise and comprehensive description of the decision maker's judgment. The relevant definitions of PIVHFs are as follows:

Given a non-empty set X, a PIVHFs H over X can be denoted as:

$$H = \{< x, h(x) > \mid x \in X\}$$

where $h(x)$ represents probabilistic interval-valued hesitant fuzzy element (PIVHFE) of variable x. The usual form for $h(x)$ is as follows:

$$h(x) = \{([l_x^{i-}, l_x^{i+}], p_x^i) \mid i = 1, 2, 3, \cdots k, p_x^i \in [0,1], \sum_{i=1}^{k} p_x^i = 1\}$$

where $[l_x^{i-}, l_x^{i+}]$ is an affiliation interval denoting the affiliation level of element X within set H. k indicating the quantity of membership intervals. l_x^{i-}, l_x^{i+} take on values from 0 to 1. p_x^i is the probability associated with $[l_x^{i-}, l_x^{i+}]$.

1) Distance measure

The existing Hemming distance between two PIVHFEs $h(x)_1$ and $h(x)_2$ is defined as:

$$d(h(x)_1, h(x)_2) = \frac{1}{2}\sum_{i=1}^{k}(| p^i_{x_1} l^{i^-}_{x_1} - p^i_{x_2} l^{i^-}_{x_2} | + | p^i_{x_1} l^{i^+}_{x_1} - p^i_{x_2} l^{i^+}_{x_2} |) \quad (1)$$

The distance measure of PIVHFE must satisfy three fundamental axiomatic requirements:

(1) Non-negativity: $d(h(x)_1, h(x)_2) \geq 0$

(2) Commutativity: $d(h(x)_1, h(x)_2) = d(h(x)_2, h(x)_1)$

(3) Reflexivity: $d(h(x)_1, h(x)_2) = 0 \Leftrightarrow h(x)_1 = h(x)_2$

We identified certain shortcomings in this distance measure. When calculating the distance between PIVHFEs $h_1 = \{[0, 0.2]0.4, [0.4, 0.8]0.6\}$ and d $h_2 = \{[0, 0.4]0.2, [0.3, 0.6]0.8\}$, the existing formula (1) yields the distance as $d(h_1, h_2) = 0$. Evidently, h_1 and h_2, represent two distinct PIVHFEs, thereby contradicting the reflexivity condition in the definition. The limitation of the existing distance measure can result in significant deviations of evaluation results from actual conditions, adversely affecting the accuracy and validity of the evaluation process. Aiming at the existing limitation, this paper presents an improved distance measure for PIVHFEs, building upon the existing distance measurement framework. The enhanced distance calculation method is detailed as follows:

$$D(h(x)_1, h(x)_2) = \frac{1}{2}\sum_{i=1}^{k}\left(|p^i_{x_1} l^{i^-}_{x_1} - p^i_{x_2} l^{i^-}_{x_2}| + |p^i_{x_1} l^{i^+}_{x_1} - p^i_{x_2} l^{i^+}_{x_2}|\right) + \frac{1}{2}\sum_{i=1}^{k}\left(|l^{i^+}_{x_1} - l^{i^+}_{x_2}| + |l^{i^-}_{x_1} - l^{i^-}_{x_2}|\right) p^i_{x_1} p^i_{x_2} \quad (2)$$

The proposed novel distance measure possesses the following properties:

(1) $0 \leq D(h(x)_1, h(x)_2)$ and $D(h(x)_2, h(x)_1) = D(h(x)_1, h(x)_2)$

Proof: The formula structure of the new distance measure for PIVHFE clearly exhibits its properties of non-negativity and commutativity.

(2) $D(h(x)_1, h(x)_2) = 0$ if and only if $h(x)_1 = h(x)_2$

Proof: Assuming $h(x)_1 \neq h(x)_2$, $\exists$ a, which makes

$$|p^a_{x_1} l^{a^-}_{x_1} - p^a_{x_2} l^{a^-}_{x_2}| + |p^a_{x_1} l^{a^+}_{x_1} - p^a_{x_2} l^{a^+}_{x_2}| = 0$$

$$(|l^{a^+}_{x_1} - l^{a^+}_{x_2}| + |l^{a^-}_{x_1} - l^{a^-}_{x_2}|) p^a_{x_1} p^a_{x_2} = 0$$

Then

$$p^a_{x_1} l^{a^-}_{x_1} = p^a_{x_2} l^{a^-}_{x_2}, \; p^a_{x_1} l^{a^+}_{x_1} = p^a_{x_2} l^{a^+}_{x_2}$$

$$(|l^{a^+}_{x_1} - l^{a^+}_{x_2}| + |l^{a^-}_{x_1} - l^{a^-}_{x_2}|) p^a_{x_1} p^a_{x_2}$$

$$= p^a_{x_2} \, | p^a_{x_2} - p^a_{x_1} | (l^{a^+}_{x_2} + l^{a^-}_{x_2}) = 0$$

Then $p^a_{x_1} = p^a_{x_2}, l^{a^+}_{x_1} = l^{a^+}_{x_2}, l^{a^-}_{x_1} = l^{a^-}_{x_2}$

Which is conflict to $h(x)_1 \neq h(x)_2$

So $D(h(x)_1, h(x)_2) = 0$ if and only if $h(x)_1 = h(x)_2$

When calculating the distance D (h_1, h_2) between h_1 and h_2 using the new distance measure, then D (h_1, h_2) = 0.08.

Additionally, the distances from h_1 to 19 other PIVHFEs were calculated using both methods, with the results shown in Fig. 1.

From Fig. 1, it is clear that the results obtained from these two distance measures demonstrate dissimilarity, specifically $D(h_i, h_j) > d(h_i, h_j)$. Therefore, the improved distance yields larger values compared to the original measure, highlighting greater distance variation and higher efficiency. In addition, when the distances between PIVHFEs are larger, the difference between the improved and original measures becomes more pronounced. Consequently, the improved measure aligns more closely with individual cognitive perceptions and enhances the ability to distinguish effectively between two PIVHFEs. This novel distance measure contributes to improving the accuracy of the assessment model.

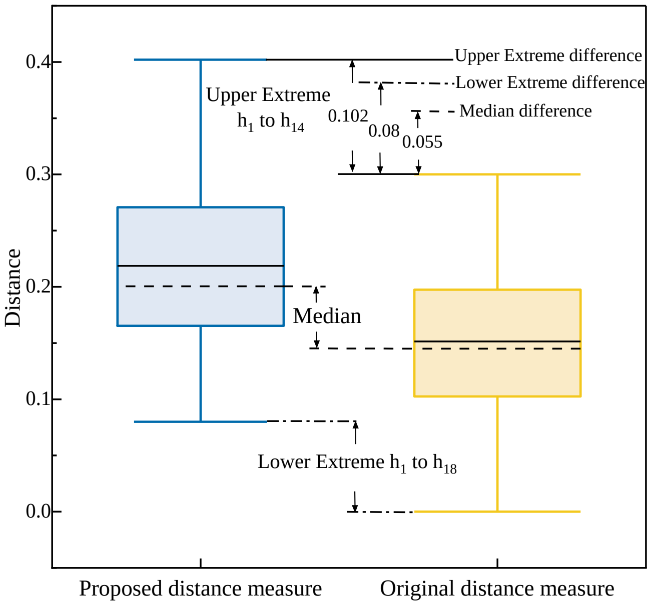


Fig. 1. Comparison of distance calculations

2) Scoring function

The existing scoring function $s(h)$ of PIVHFE $h(x) = \{([l_x^{i-}, l_x^{i+}], p_x^i) \mid i = 1, 2, 3, \cdots k\}$ is defined as:

$$s(h) = \sum_{i=1}^{k} \frac{l_x^{i-} + l_x^{i+}}{2} p_x^i \quad (3)$$

To ensure the transitivity of PIVHFs, the deviation function of PIVHFEs is introduced:

$$V(h) = \sqrt{\sum_{i=1}^{k} \left(\frac{l_x^{i-} + l_x^{i+}}{2} - s(h)\right)^2 p_x^i} \quad (4)$$

With $s(h)$ being the scoring function of $h(x)$.

We used the existing scoring function and deviation function to determine the dominance of $h_1 = \{[0.1, 0.3]0.4, [0.4, 0.8]0.6\}$ over $h_0 = \{[0, 0.4]0.4, [0.5, 0.7]0.6\}$ results in $s(h_1) = s(h_0) = 0.44$ and $V(h_1) = V(h_0)$. To mitigate potential shortcomings in the scoring function that could lead to evaluation result deviations, this paper proposes a new scoring function $S(h)$ based on the deviation of PIVHFEs:

$$S(h) = \left(1 - \sum_{i=1}^{k} [(l_x^{i-} - \bar{h})^2 + (l_x^{i+} - \bar{h})^2] p_x^i\right) \sum_{i=1}^{k} \frac{l_x^{i-} + l_x^{i+}}{2} p_x^i \quad (5)$$

where $\bar{h} = \sum_{i=1}^{k} \frac{l_x^{i-} + l_x^{i+}}{2} p_x^i$ is the mean value of the PIVHFE.

This innovative scoring approach simultaneously considers the spread of the membership interval (through its boundary values) and the mean value of PIVHFEs. This deviation score ensures that the score assigned to each PIVHFE fully reflects the information it contains.

The deviation scores of h_1-h_{20} are calculated using the novel score function.

The experimental results are presented in Figure 2, which demonstrates that the variance-based scoring method effectively distinguishes the sizes of PIVHFEs. Notably, it overcomes the shortcomings of the existing scoring method when comparing h_4-h_5 and h_8-h_9. Therefore, the proposed scoring method is more suitable for decision-making scenarios.

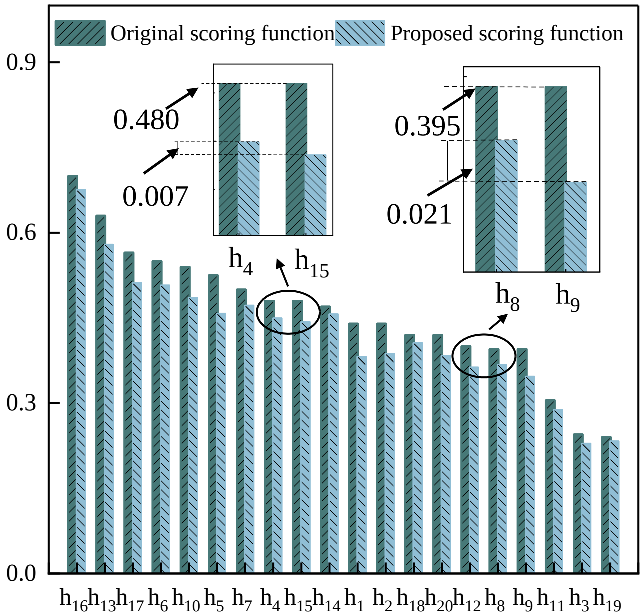


Fig. 2. Comparison of Score Calculation Results

B. *Hesitant fuzzy entropy weighting method*

In this subsection, we integrate the probability interval-value hesitant fuzzy entropy with the improved entropy weight method to propose a novel weighting method for PIVHFs.

In multi-attribute decision-making problems where assessment information is represented by PIVHFEs, determining the weights of indicator attributes is crucial for accurate decision-making outcomes. The existing entropy weight method, which relies on precise numerical values, evaluates the dispersion of indicators using information entropy values to assign weights. To quantify the entropy of PIVHFEs, Zhu et al. [23] introduced a novel approach to accurately measure uncertainty. They developed a new type of PIVHF entropy measure, based on distance measure and pseudo-distance measure of PIVHFE. The distance-type entropy measure of PIVHFE $h(x)=\{([l_x^{i^-},l_x^{i^+}],p_x^i)\,|\,i=1,2,3,...,k\}$ can be expressed as:

$$E(h)=(1-\xi)E_1(h)+\xi E_2(h)=1-2\xi\,|\,\mathrm{s(h)}-0.5\,|-(1-\xi)\sum_{i=1}^{k}(|l_x^{i^-}-0.5|+|l_x^{i^+}-0.5|)p_x^i \tag{6}$$

where ξ is the tradeoff coefficient and usually $\xi\in(0,1)$; $E_1(h)$ is the distance entropy measure and $E_2(h)$ is the pseudo-distance entropy measure.

We incorporate the developed entropy metric into the refined entropy-based weighting framework, thereby enhancing the accuracy of weight assignment processes. In addition, to address the limitation that the traditional entropy weighting method becomes biased when the entropy value approaches 1, we integrate this entropy measure with the improved entropy weighting method proposed by Wu. et al [24]. The operational procedure of this approach consists of the following steps:

Given a multi-attribute decision problem with a set of alternatives as $A_i(i=1,2,3,\cdots m)$, a set of criteria $C_j(\mathrm{j}=1,2,3,\cdots n)$, and experts making an evaluation matrix of the metrics $R=(h_{ij})_{m\times n}$

Step 1: Normalize the evaluation matrix $R=(h_{ij})_{m\times n}$, to obtain the normalized matrix $N=(h'_{ij})_{m\times n}$:

$$N=\begin{pmatrix} \{[l_{x_1}^{r1-},l_{x_1}^{r1+}]\,|\,p_{x_1}^{r1}\}_{a_1} & \{[l_{x_2}^{r1-},l_{x_2}^{r1+}]\,|\,p_{x_2}^{1}\}_{a_2} & \cdots & \{[l_{x_n}^{r1-},l_{x_n}^{r1+}]\,|\,p_{x_n}^{r1}\}_{a_n} \\ \{[l_{x_1}^{r2-},l_{x_1}^{r2+}]\,|\,p_{x_1}^{r2}\}_{a_1} & \{[l_{x_2}^{r2-},l_{x_2}^{r2+}]\,|\,p_{x_2}^{r2}\}_{a_2} & \cdots & \{[l_{x_n}^{r2-},l_{x_n}^{r2+}]\,|\,p_{x_n}^{r2}\}_{a_n} \\ \vdots & \vdots & \ddots & \cdots \\ \{[l_{x_1}^{rm-},l_{x_1}^{rm+}]\,|\,p_{x_1}^{rm}\}_{a_1} & \{[l_{x_2}^{rm-},l_{x_2}^{rm+}]\,|\,p_{x_2}^{rm}\}_{a_2} & \cdots & \{[l_{x_n}^{rm-},l_{x_n}^{rm+}]\,|\,p_{x_n}^{rm}\}_{a_n} \end{pmatrix}$$

where a is the base of the PIVHFE h'_{ij}.

Step 2: Calculate the PIVHF entropy $E(h'_{ij})$ for each criterion and the entropy value $E(\mathrm{C}_j)$ by:

$$E(h'_{ij})=1-2\xi\,|\,s(h'_{ij})-0.5\,|-(1-\xi)\sum_{r=1}^{a_j}(|l_{x_j}^{ri^-}-0.5|+|l_{x_j}^{ri^+}-0.5|)p_{x_j}^{ri} \tag{7}$$

$$E(\mathrm{C}_j)=\frac{1}{m}\sum_{i=1}^{m}E(h'_{ij}) \tag{8}$$

where $\xi\in(0,1)$ is the trade-off coefficient and $s(h'_{ij})$ is the original score function of h'_{ij}

Step 3: Calculate the entropy weight w_j for each criterion by:

$$w_j=\begin{cases} \dfrac{1-E(\mathrm{C}_j)+\bar{E}^l}{\sum\limits_{k=1,E(C_k)\neq 1}^{n}(1-E(C_k)+\bar{E}^l)} & E(C_j)<1 \\ 0 & E(C_j)=1 \end{cases} \tag{9}$$

where $\bar{E}$ is the mean of the entropy values of all criteria except 1, and l is the coefficient related to precision, $l=41.27$.

C. *PIVHF-TODIM method for potential ranking*

In this subsection, we propose an adapted TODIM decision-making method tailored for PIVHFEs. As an established method in multi-attribute decision analysis, TODIM integrates principles from prospect theory while accounting for the cognitive and psychological dimensions of decision-making processes [25]. Considering the psychological factors involved in expert decision-making, the TODIM framework provides a robust mechanism for aligning computational results with actual decision-making practices in complex scenarios. When the evaluation values of program attributes are represented as PIVHFEs, traditional TODIM methods require enhancements. The implementation of the proposed approach involves the following systematic process:

It is assumed that there exist m regional power grid alternatives, represented as $A_i(i=1,2,3,...m)$. Each alternative has n criteria, represented as $C_j(j=1,2,3,...n)$. The decision matrix $H=(h_{ij})_{m*n}$ is determined from the expert evaluation results. h_{ij} is the evaluation information in the form of PIVHFE.

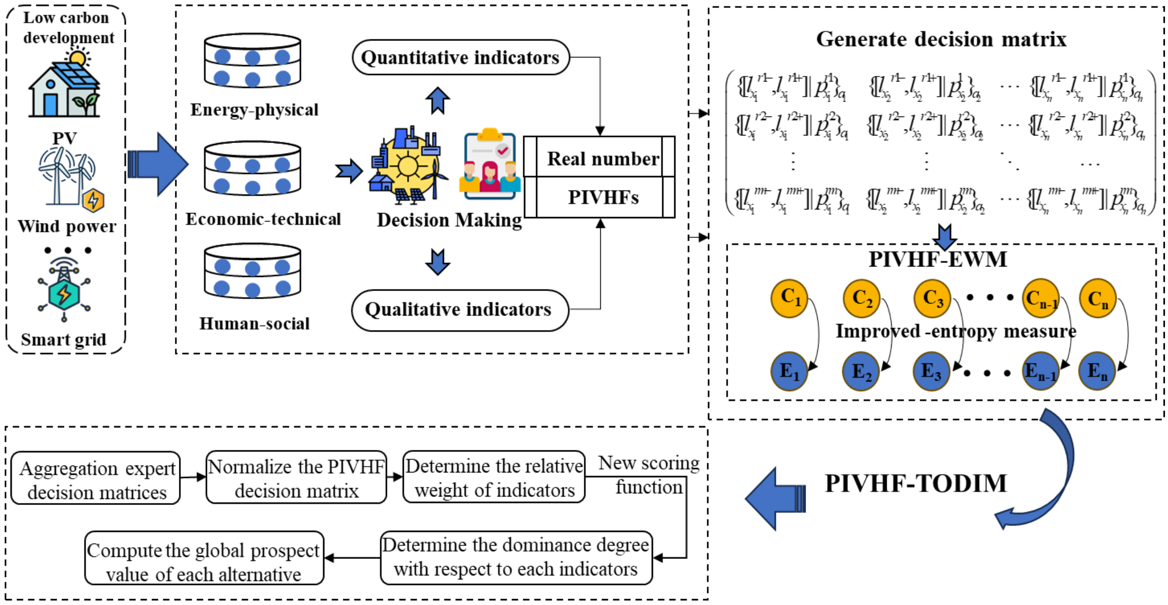


Fig. 3. Flow chart of the research framework

Step 1: Utilize the probabilistic splitting method [23] to standardize the initial matrix H. This ensures that the PIVHFEs under each indicator are based on the same foundation, with interval affiliations ordered in reverse, resulting in a standardized decision matrix $\overline{H}$:

$$\overline{H}=\begin{pmatrix}\{[l_{x_1}^{r1-},l_{x_1}^{r1+}]|\,p_{x_1}^{1}\}_{a_1} & \{[l_{x_2}^{r1-},l_{x_2}^{r1+}]|\,p_{x_2}^{1}\}_{a_2} & \cdots & \{[l_{x_n}^{r1-},l_{x_n}^{r1+}]|\,p_{x_n}^{1}\}_{a_n}\\ \{[l_{x_1}^{r2-},l_{x_1}^{r2+}]|\,p_{x_1}^{r2}\}_{a_1} & \{[l_{x_2}^{r2-},l_{x_2}^{r2+}]|\,p_{x_2}^{r2}\}_{a_2} & \cdots & \{[l_{x_n}^{r2-},l_{x_n}^{r2+}]|\,p_{x_n}^{r2}\}_{a_n}\\ \vdots & \vdots & \ddots & \cdots\\ \{[l_{x_1}^{rm-},l_{x_1}^{rm+}]|\,p_{x_1}^{rm}\}_{a_1} & \{[l_{x_2}^{rm-},l_{x_2}^{rm+}]|\,p_{x_2}^{rm}\}_{a_2} & \cdots & \{[l_{x_n}^{rm-},l_{x_n}^{rm+}]|\,p_{x_n}^{rm}\}_{a_n}\end{pmatrix}$$

Step 2: Calculate the weight value $w_j\,(j=1,2,\cdots n)$ of each criterion attribute $C_j\,(j=1,2,\cdots n)$ using hesitant fuzzy entropy weighting method (Eq. 8-10)

Step 3: The maximum weight value is selected as the reference weight w_r , the corresponding relative weights w_{jr} are determined through the following calculation:

$$w_{jr}=\frac{w_j}{w_r},\ j=1,2,3,\cdots n \tag{10}$$

w_j is the indicator weight, $w_r=\max\{w_j\mid j=1,2,3,\cdots n\}$

Step 4: Calculate the dominance degree $\vartheta(A_i,A_k)$ of regional power grid A_i over other regional power grid A_k :

$$\vartheta(A_i,A_k)=\sum_{j=1}^{n}\varphi_j(A_i,A_k),\mathrm{i,k}=1,2,3,\cdots m \tag{11}$$

$$\varphi_j(A_i,A_k)=\begin{cases}\sqrt{w_{jr}D(h'_{ij},h'_{kj})/\sum_{j=1}^{n}w_{jr}} & S(h'_{ij})>S(h'_{kj})\\ 0, & S(h'_{ij})=S(h'_{kj})\\ -\frac{1}{\theta}\sqrt{(\sum_{j=1}^{n}w_{jr})D(h'_{ij},h'_{kj})/w_{jr}} & S(h'_{ij})<S(h'_{kj})\end{cases} \tag{12}$$

where θ represents the attenuation coefficient, reflecting the decision maker's degree of risk aversion. $D(h'_{ij},h'_{kj})$ and $S(h'_{ij})$ are the distances and scores of h'_{ij} and h'_{kj}. w_{jr} is the relative weight of indicator C_j.

Step 5: Compute the total dominance of each regional power grid based on the degree of relative dominance $\Phi(\mathrm{A}_i)$

$$\Phi(\mathrm{A}_i)=\frac{\sum_{k=1}^{m}\vartheta(\mathrm{A}_i,\mathrm{A}_k)-\min_i\{\sum_{k=1}^{m}\vartheta(\mathrm{A}_i,\mathrm{A}_k)\}}{\max_i\{\sum_{k=1}^{m}\vartheta(\mathrm{A}_i,\mathrm{A}_k)\}-\min_i\{\sum_{k=1}^{m}\vartheta(\mathrm{A}_i,\mathrm{A}_k)\}},i=1,2,\cdots,m \tag{13}$$

$\vartheta(A_i,A_k)$ represents the dominance degree of A_i compared with other A_k

Step 6: Rank the alternatives according to their total dominance degree $\Phi(\mathrm{A}_i)$ in order to identify the optimal option.

The research methodology of this paper is shown in the flow chart (Fig.3)

IV. CASE STUDY

A. *Perceived potential for green development of regional power grids*

New urbanization areas are pivotal areas for implementing China's modernization and reform strategy. In response to this national strategy, the Shanghai Municipal Government has introduced specific policy measures to accelerate urban development during the 14th Five-Year Plan period, emphasizing low-carbon planning and sustainable growth in emerging urban areas. These regions are marked by extensive coverage and notable disparities in development, posing significant challenges for the green development planning of regional power grids.

Urban development serves as a crucial driver of sustainable growth, yet it frequently encounters resource constraints. Conducting comprehensive assessments of GD potential in urban power grids is therefore imperative. These analyses offer valuable insights and strategic guidance for implementing low-carbon initiatives in urban grid management systems. In this study, we focus on the new urbanization regions of Shanghai specified in the 'Opinion': Qingpu District (G_1), Pudong District (G_2), Jinshan District (G_3), Fengxian District (G_4), and Jiading District (G_5). we consulted five experts to evaluate various alternatives. The expert panel comprised professionals from Shanghai's newly urbanized areas, representing sectors such as finance, operations, logistics, regulation, and markets. For each regional power grid, the expert panel provided evaluation opinions on 15 green development criteria. The decision-making results provided by the experts were transformed into PIVHFEs. Scores for different regional grids were calculated under each criterion to obtain clear and intuitive evaluation information. The PIVHF decision-making information is presented in Figure 4.

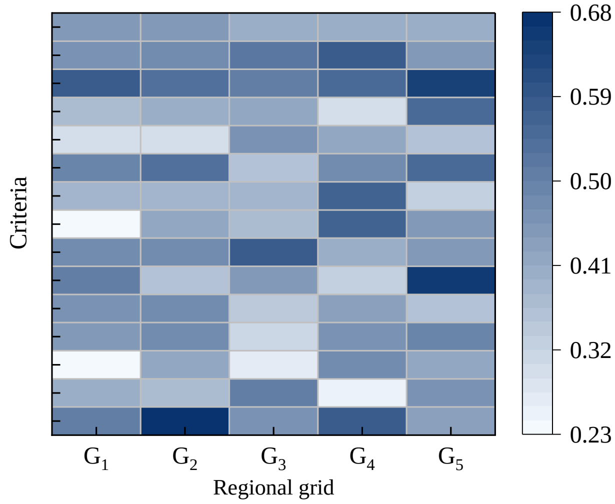


Fig. 4. PIVHF decision-making information heat map

In the following, we apply the developed PIVHF-TODIM approach to determine the ranking of alternative grids. The methodological procedure is systematically presented as follows:

Step1: The initial decision matrix is standardized using the probabilistic split method, ensuring a consistent base for PIVHFEs across all criteria. As lower grid energy consumption levels and reduced line losses signify higher green development potential, criteria C_5 (grid energy consumption level) and C_9 (regional grid network loss management) are transformed into benefit-type criteria. A portion of the standardized decision-making data is provided in TABLE I.

TABLE I
STANDARDIZED PROBABILISTIC INTERVAL-VALUED HESITANT FUZZY DECISION INFORMATION

Regional grid	C_1	C_7	C_{13}
G_1	[0.6,0.8]0.5 [0.5,0.6]0.3 [0,0.5]0.2	[0.6,0.8]0.3 [0.4,0.6]0.3 [0.3,0.4]0.4	[0.6,0.9]0.6 [0.5,0.6]0.2 [0.3,0.4]0.2
G_2	[0.7,0.9]0.5 [0.58,0.7]0.3 [0.5,0.58]0.2	[0.7,0.9]0.4 [0.4,0.5]0.4 [0.1,0.3]0.2	[0.7,0.8]0.6 [0.4,0.7]0.2 [0.1,0.3]0.2
G_3	[0.6,0.9]0.5 [0.4,0.5]0.3 [0,0.3]0.2	[0.7,0.9]0.2 [0.6,0.7]0.5 [0.3,0.5]0.3	[0.6,0.7]0.6 [0.4,0.6]0.2 [0.2,0.3]0.2
G_4	[0.7,0.8]0.5 [0.5,0.7]0.3 [0.2,0.5]0.2	[0.6,0.7]0.4 [0.4,0.6]0.2 [0.1,0.3]0.4	[0.7,0.8]0.6 [0.4,0.5]0.2 [0.2,0.4]0.2
G_5	[0.6,0.8]0.5 [0.2,0.5]0.3 [0.1,0.2]0.2	[0.5,0.8]0.6 [0.3,0.4]0.1 [0.2,0.3]0.3	[0.62,0.8]0.6 [0.56,0.62]0.2 [0.5,0.56]0.2

Step2: The entropy measure of all PIVHFEs is computed using Equation (7). The weights w_j and the relative weights w_{jr} are calculated using Equations. (8–10). The trade-off coefficient $\xi = 0.5$.

Step3: Using Equation (12) with θ=0.5, we calculate the dominance degree of each regional grid G_i over other regional grids G_k across all green development indicators C_j. The relative dominance matrices $\varphi_j(G_i, G_k)$ are partially presented below:

$$\varphi_1(G_i, G_k) = \begin{pmatrix} 0.000 & 0.113 & -2.379 & 0.076 & -2.664 \\ -3.182 & 0.000 & -3.400 & -2.358 & -3.984 \\ 0.084 & 0.121 & 0.000 & 0.114 & -2.379 \\ -2.136 & 0.084 & -3.198 & 0.000 & -3.211 \\ 0.095 & 0.141 & 0.084 & 0.114 & 0.000 \end{pmatrix}$$

$$\varphi_7(G_i, G_k) = \begin{pmatrix} 0.000 & 0.122 & 0.124 & -3.717 & -5.295 \\ -4.431 & 0.000 & 0.155 & -3.889 & -4.616 \\ -4.509 & -5.638 & 0.000 & -5.500 & -6.669 \\ 0.102 & 0.107 & 0.151 & 0.000 & 0.118 \\ 0.146 & 0.127 & 0.183 & -4.290 & 0.000 \end{pmatrix}$$

$$\varphi_{13}(G_i, G_k) = \begin{pmatrix} 0.000 & -2.924 & -2.689 & -2.689 & 0.090 \\ 0.107 & 0.000 & -2.564 & 0.059 & 0.103 \\ 0.098 & 0.094 & 0.000 & 0.094 & 0.103 \\ 0.098 & -1.622 & -2.564 & 0.000 & 0.096 \\ -2.460 & -2.832 & -2.832 & -2.640 & 0.000 \end{pmatrix}$$

Step4: Using Equation (13), we calculate the overall dominance degree by aggregating various criteria for each regional grid. The results are as follows: $\Phi(G_1) = 0.159$, $\Phi(G_2) = 1$, $\Phi(G_3) = 0$, $\Phi(G_4) = 0.381$, $\Phi(G_5) = 0.788$.

Thus, Pudong District (G_2) is the regional grid with the highest potential for green development. The ranking of all five regional grids should be $G_2 \succ G_5 \succ G_4 \succ G_1 \succ G_3$.

B. *Results analysis*

In this subsection, we conducted a practical analysis to evaluate the effectiveness and real-world applicability of the obtained results. The weighting coefficients for hierarchical evaluation criteria were calculated, with the corresponding quantitative results represented in Figure 5.

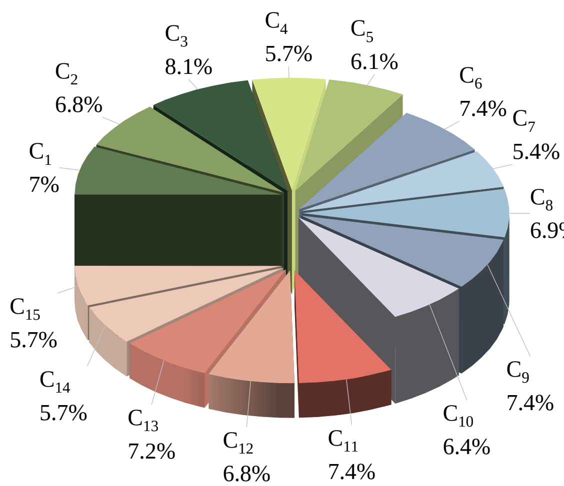


Fig. 5. Weighting results for each criterion

From Fig. 5, it shows that the energy-physical dimension has the highest weight. This highlights the importance of promoting new energy consumption as a key factor in the low-carbon development of RGs. Among its sub-indicators, the C_1 and C_3 are given considerable weight, reflecting the requirement for Shanghai districts to meet renewable energy consumption targets set by municipal authorities. For economic-technical dimension, grid loss management (C_9) is more heavily weighted. This highlights the direct impact that increased investment in line infrastructure and reduced losses have on the GD of RGs [26]. In the human-social dimension, C_{11} holds significant weight. This emphasizes the urgent need for regional power grids to prioritize the collection and transparency of carbon information. This practice aids in supervising and guiding regional power grids toward achieving green development.

In addition, the weights of human-social criteria are on par with those of other primary indicators. The weighting result underscores the significant influence of social factors on the GD of RGs. These findings validate the rationality of the constructed indicator system and the weight calculation method for assessing the GD potential of RGs presented in this paper.

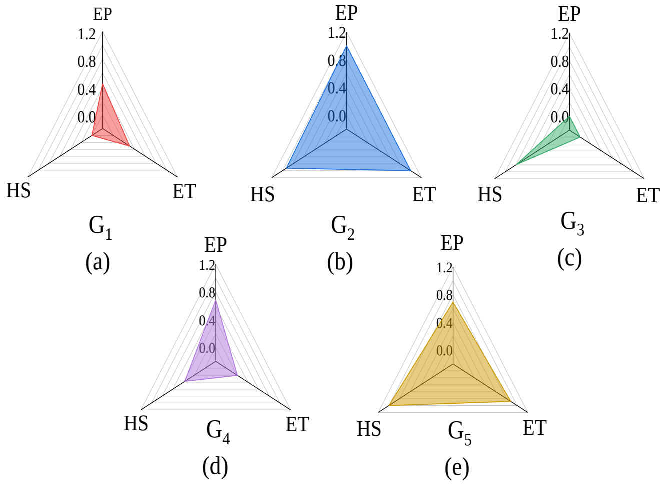


Fig. 6. Radar chart of the dominance degree of first-tier indicators

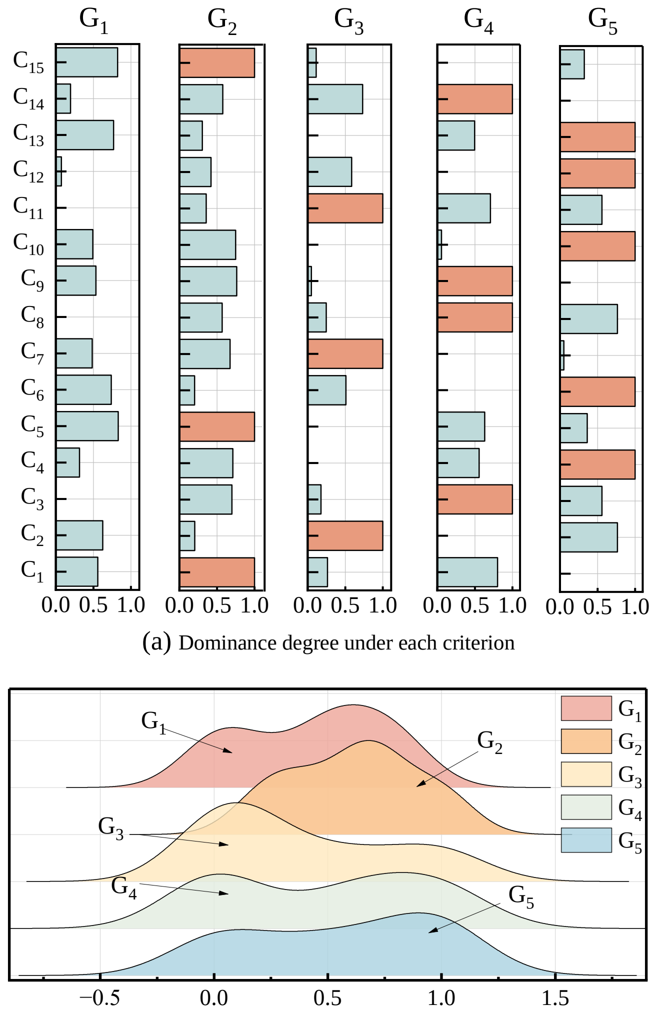
Through systematic model simulations, we evaluated the integrated superiority levels of regional power grids in multiple key dimensions. The calculation results are illustrated in Figure 6.

From Fig. 6, it shows that G_5 and G_2 exhibit significant advantages over the other four regions. In practical terms, G_2 encompasses a vast geographical area, characterized by numerous newly developed urban zones and pilot projects for grid-based construction. G_5 demonstrates advanced urban development and strong financial capacity. Its power grid infrastructure is more developed than that of the newly urbanized areas of Qingpu (G_1) and Jinshan (G_3). Hence, G_5 demonstrates exceptional performance in the social and economic dimensions, as reflected in the evaluation results.

Conversely, G_4, G_1, and G_3 show relatively low comprehensive GD potential. These regions exhibit lower urbanization rates and encompass extensive older urban and rural power grids. Constrained by regional development and green growth objectives, these grids urgently require rational planning and low-carbon upgrades. The evaluation results indicate that these power grids demonstrate relatively poor performance across the economic, technical, and energy-physical dimensions.

The results demonstrate significant consistency with the empirical characteristics of regional power grids, providing robust verification of the evaluation framework's validity.

We further calculated the dominance degrees of each regional power grid under various criteria. The normalized dominance values and their corresponding distributions are illustrated in Figure 7(a-b).



(b) Ridge map of dominance distribution

Fig. 7. Degree of dominance under each indicator

From Fig.7, it can be seen that each new urbanization area in Shanghai possesses unique strengths in green power grid construction and management. Regional power grids with lower rankings in GD potential exhibit fewer advantageous attributes. A notable negative correlation emerges between the ranking of green development potential and the prevalence of advantageous criteria within regional power grids.

Specifically, the regional power grid G_2 exhibits a distinct advantage across various criteria, demonstrating a significantly higher degree of superiority across most criteria. The public disclosures from State Grid Shanghai Pudong Electric Power Company confirm this result. The disclosures highlight the extensive efforts undertaken by the Pudong District Grid to integrate distributed photovoltaic (PV) systems. Notably, in 2022, the region achieved an annual increase in PV grid-connected installed capacity of 58.4 MW. This growth rate surpasses Shanghai's overall municipal achievement by 22%. Consequently, G_1 demonstrates superior performance metrics, particularly in distributed generation capacity integration and renewable energy utilization efficiency.

In 2023, the average outage time for Jiading urban customers was 0.05 hours per household. This is 0.05 hours shorter than the average outage time for Shanghai urban customers. The average outage time for Jiading urban customers was 0.11 hours per household, significantly lower than the Shanghai city average of 0.39 hours. The regional grid G_5 excels in criteria such as the grid safety operation level and operation and maintenance efficiency

The regional grid G_4 exhibits notable strengths in both renewable energy consumption rates and network loss management. Data from the State Grid Shanghai Fengxian Power Supply Company indicates a line loss rate of just 2.07% in 2022, supporting this assessment. Despite these strengths, there are still opportunities for improvement, particularly in the adoption of emerging technologies. Conversely, the regional grids in Qingpu (G_1) and Jinshan (G_3) Districts demonstrate fewer criteria with notable superiority.

Based on the above analysis, the proposed ranking approach effectively identifies the determinants of GD in regional power grids. Furthermore, it facilitates the formulation of tailored development strategies that align with the unique advantages and challenges of each locale. It ensures that development strategies are context-specific, which promotes sustainable and efficient grid operations tailored to each region's unique needs and conditions.

C. Sensitivity analysis of parameter θ

This subsection conducts a comprehensive sensitivity analysis to examine the impact of parameter θ. The parameter θ in the TODIM framework serves as a crucial indicator for quantifying and interpreting decision-makers' psychological tendencies toward risk avoidance. When $0<\theta<1$, it indicates that decision makers exhibit heightened sensitivity to losses associated with low dominance degrees. Conversely, $\theta>1$ signifies that the distress experienced by decision makers in response to losses is diminished. Referring to the methodology in [27], we select θ=0.5, θ=0.8, θ=2, and θ=4, to observe the variations in the results. The calculation results are presented in Table II.

TABLE II
GLOBAL PROSPECT VALUE OF GI WITH DIFFERENT VALUES OF Θ

θ value	G_1	G_2	G_3	G_4	G_5
θ=0.5	0.1592	1.0000	0.0000	0.3806	0.7882
θ=0.8	0.1541	1.0000	0.0000	0.3806	0.7921
θ=1	0.1509	1.0000	0.0000	0.3805	0.7945
θ=2	0.1352	1.0000	0.0000	0.3803	0.8062
θ=4	0.1077	1.0000	0.0000	0.3799	0.8268

As demonstrated in Table II, it reveals that, as θ increases, the global prospective values of G_1, G_4 decrease, whereas G_5 increases.

Comparing the magnitude of changes in overall dominance with respect to θ, G_1 exhibit greater sensitivity to variations in the parameter θ. The dominance degree of G_1 exhibited a significant variation of 32.35%, while G_4 showed minimal change at 0.01%. The variations in global dominance degrees indicate that increased loss acceptance levels lead to reduced comprehensive dominance disparities among alternatives.

In addition, we compare the dominance degrees of regional grids G_1 and G_5 relative to other regional power grids under C_1, C_3, and C_6, as illustrated in Fig.8.

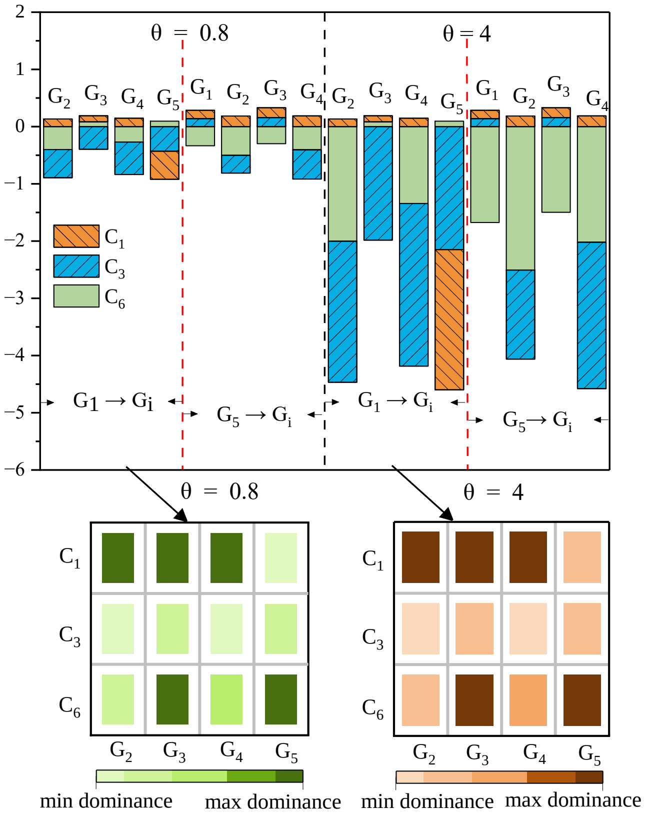


Fig 8. The dominance degree of G_5 over other G_i with θ=4.

As illustrated in Fig.8, the losses of G_5 relative to the other regional power grids G_i predominantly occur in C_6 and C_1, whereas the losses of G_1 are most pronounced in C_3. When θ=0.8, the losses for G_1 and G_5 are amplified, with G_1 experiencing significantly greater losses than G_5. This results in a higher overall dominance for G_5. At θ=4, although the losses for G_1 and G_5 are diminished, their respective advantages remain insufficient to offset these losses. Additionally, the results indicate that fluctuations in the parameter θ do not alter the overall ranking of the regional power grids.

The above analysis demonstrates that the decision outcomes maintain their robustness regardless of fluctuations in decision-makers' risk aversion thresholds. G_2 is consistently regarded as the regional power grid with the highest green development potential, underscoring the robustness of the method. It is also observed that the sensitivity of the parameters is influenced by the evaluation information. Specifically, the smaller the differences in the evaluation information, the more sensitive the ranking results are to changes in the parameters.

D. Sensitivity analysis of weighting coefficient ζ

This subsection is dedicated to a comprehensive sensitivity analysis of parameter ζ, with particular emphasis on its role and effects within the decision-making framework. According to Equation (6), the weighting coefficient ζ represents the degree of preference for the overall or interval discretization of the PIVHFE. This section examines the impact of ζ on the perception of low-carbon development potential when θ=1.The variation of global dominance degree with respect to the ζ value is shown in Figure. 9.

From Fig. 9, it is evident that as ζ increases, the global dominance of G_1 rises, while the global dominance of all other regional grids declines. According to Equation (6-9), an increase in ζ leads to greater consideration of the differences between the probabilistic hesitant fuzzy meta-means. This suggests that regional power grid G_1 performs better under conditions of higher overall uncertainty. In contrast, other regional grids exhibit greater dominance when expert opinions show higher divergence. The analytical results further demonstrate that the ranking order of regional power grids remains consistent across different values of parameter ζ.

The above analysis demonstrates that, as the parameter ζ is changed, the dominance degree of alternatives also changes, but the ranking result does not change. This further indicates the robustness of the proposed methodology.

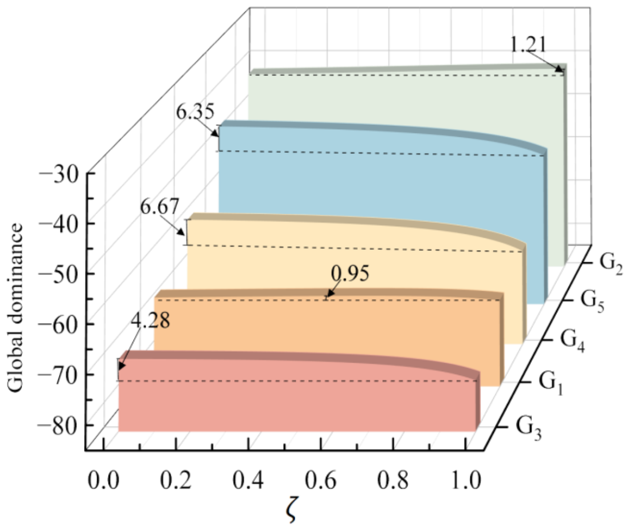


Fig9. The dominance degree of G_i with ζ

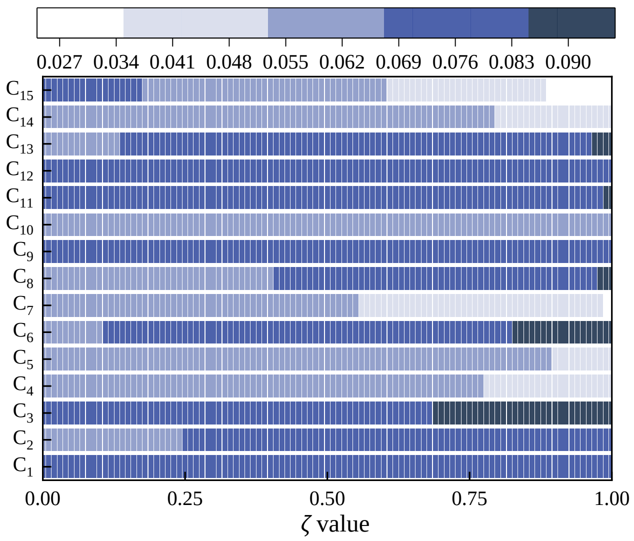


Fig10. The weighting result with ζ

Fig. 10 depicts the changes in the weight of each criterion as ζ changes. Figure 10 clearly demonstrates that, with the variation of ζ, the standard weight distribution becomes more polarized. When parameter ζ tends toward 0, the weight values are concentrated within the range of 0.06 to 0.08. As ζ approaches 1, the range of weight values expands to 0.02 to 0.1. This indicates a significant disparity in the interval uncertainty across different decision information. The inclusion of the ζ value helps balance the consideration of uncertainty, mitigating the impact of hesitation differences on the evaluation process. The preceding analysis demonstrates that the developed weighting approach successfully overcomes the constraints of conventional methods, while enhancing the rationality and effectiveness of decision information processing.

E. Comparative analysis

In this subsection, a comparative analysis is conducted by evaluating various established weighting and ranking methods.

1) Comparison of Weighting Methods

Here, to empirically verify the superiority of the proposed weighting framework, comprehensive comparative evaluations were performed against benchmark methods, including the entropy weighting system and coefficient of variation technique. Fig. 11 illustrates the differences in attribute weights resulting from the various weighting measures.

From Fig. 11. It is clear that, the weighting results derived from the proposed method demonstrate greater overall stability. The proposed weighting method accounts for the uncertainty of PIVHFEs in relation to their mean values and intervals. This approach yields stable weight distributions that emphasize key indices while mitigating the risk of extreme weight allocations.

In contrast, the weights derived from the original entropy weighting method and coefficient of variation method exhibit greater variance. These methods require converting PIVHFE into precise numerical values. This conversion process can result in a loss of critical decision-making information, thereby affecting the assignment outcomes. These traditional methods prioritize the numerical characteristics of the indicators. Therefore, the assignment outcomes are disproportionately influenced by criteria with higher information entropy or standard deviation.

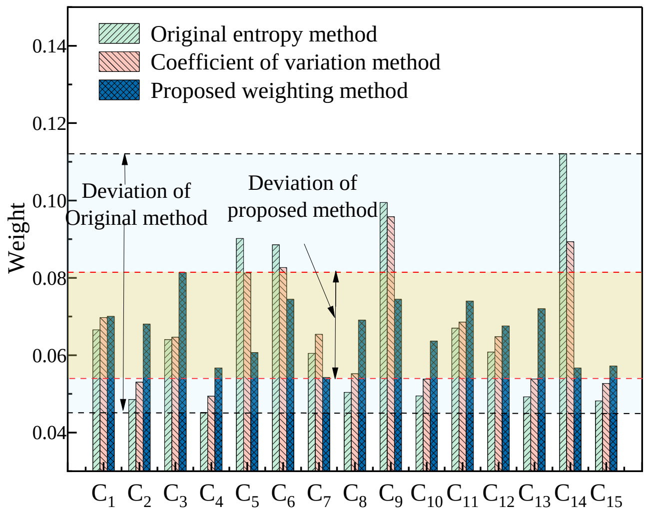


Fig 11. Comparison of weighting results

Fig. 12 presents the differences in the decision-making results obtained by weight measurement methods mentioned in this section. As clearly illustrated in Figure 12, while the ranking remained consistent across different weighting methods, there were notable differences in dominance degree.

In the evaluation of G_5 and G_2, the proposed method demonstrated a relatively clear distinction in dominance. The proposed method yields a dominance difference of 12.47 between G_5 and G_2, whereas the comparative methods produce differences all below 10.00. This is primarily because the proposed method is less sensitive to extreme evaluation values. The assessment of G_5 revealed minimal variation in dominance degrees across comparative methods, demonstrating a difference of merely 0.07. The traditional weighting method does not account for the impact of hesitation uncertainty on the weight measurement of PIVHFE. Therefore, there is little difference between original entropy weighting and coefficient of variation methods. The above analysis demonstrates that the proposed method not only effectively addresses the shortcomings of existing weight measurement approaches, but also handles hesitant fuzzy information more effectively.

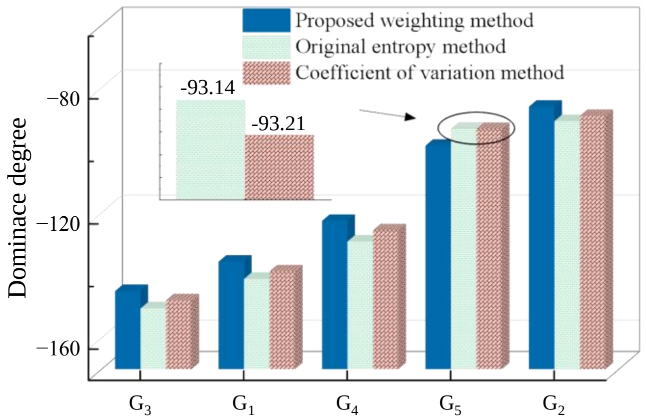


Fig 12. The comprehensive dominance with weighting methods

2) Comparison of ranking approach

Here, we compared the proposed methodology with conventional approaches, demonstrating its improved effectiveness and advanced performance characteristics. We uniformly use the weights in section A and θ=0.5. The ranking results are presented in Figure 13.

From Fig. 13, it shows that the results of the proposed approach differ in the rankings of G_1 and G_3 compared to those obtained using the classical TODIM approach. This difference originates from the utilization of a novel PIVHF distance measure in this proposed approach to calculate the combined distance between decision units. This distance metric pair incorporates the computation of interval membership and the probability of membership. In contrast, the classical TODIM ranking approach relies on linear benefit functions and singular decision criteria, which introduces biases into the process of utilizing decision information. This results in different ranking results. For the ordinary PIVHF-TODIM approach, the approach presented in this paper is consistent with its ranking outcomes. However, there is a notable difference in overall dominance. This divergence arises from variations in the computation of PIVHF distances and scores. The ordinary PIVHF-TODIM approach inadequately captures the psychological intricacies associated with the low-carbon development potential of regional grids. Furthermore, the proposed approach offers superior capabilities in discerning the nuances between different alternatives. For instance, when employing the proposed approach in place of the Ordinary PIVHF-TODIM, there is a more pronounced disparity in the overall dominance between G_1 and G_4. The extended TODIM method improves the accuracy of practical decision-making by adopting a more refined approach to calculating outlook values. This advancement provides policymakers with more precise and reliable decision support.

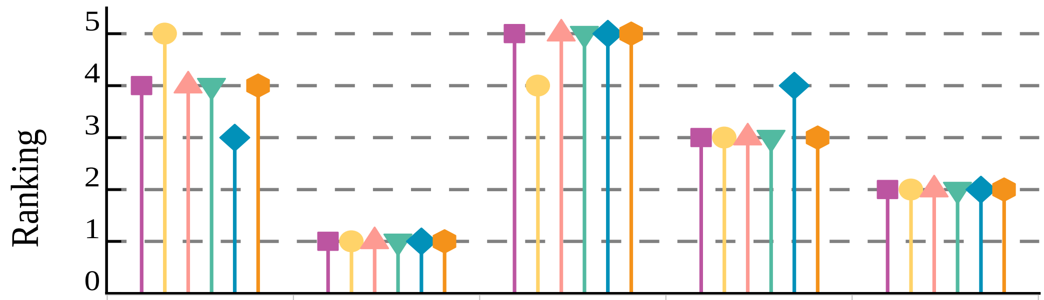
In addition to the TODIM method, various other approaches are available for addressing complex decision-making problems. This study primarily focuses on comparing three well-known methods: TOPSIS, VIKOR, and PROMETHEE. The findings are presented in. Fig 11 indicates that G_2 consistently emerges as the regional grid with the highest potential for low-carbon development. G_3 is consistently ranked lower across various methods. Although the ranking results are similar, there are notable differences in the characteristics of the various methods.

(a) A primary assumption of the TOPSIS methodology is the independence of criteria, which results in a lack of consideration for the interrelationships among criteria. In contrast, the proposed approach incorporates the uncertainty and psychological factors of decision-making process. The proposed approach is designed to accommodate decision-making scenarios characterized by complex correlations or high uncertainty among criteria. It achieves this by conducting comparisons within the framework of the same criterion.

(b) It is noteworthy that the rankings obtained using the VIKOR method exhibit some differences from those derived from the approach presented in this paper. This discrepancy primarily arises because the VIKOR method assumes that decision-makers are fully rational. Consequently, when DMs exhibit bounded rationality, the results from the VIKOR method may deviate from actual scenarios. Furthermore, the VIKOR method fails to effectively distinguish between the utility values of G_1 and G_4 for the decision-maker. In comparison, the proposed method exhibits superior power in establishing priority rankings among alternatives. The VIKOR method, when contrasted with our approach, shows substantially reduced differentiation capacity in distinguishing between alternative solutions.

(c) Lastly, the PROMETHEE method is a ranking technique that relies on preference functions. This approach's primary advantage resides in its flexibility to incorporate multiple varieties of preference functions effectively. However, the results obtained using PROMETHEE are highly dependent on the specified preference functions, which introduces a degree of subjectivity on the part of the decision-maker. In contexts characterized by high uncertainty, the proposed methodology is more suitably aligned.

In conclusion, the proposed method offers a more comprehensive consideration of the psychological factors influencing decision-makers. It better reflects their true perspectives in decision-making compared to traditional ranking methods. Furthermore, the methodology provides a robust framework for evaluating the GD potential of regional grids. It integrates a novel perspective value calculation method and incorporates realistic factors into the assessment process, thereby enabling more precise and reliable assessment of the GD potential of RGs.



	G_1	G_2	G_3	G_4	G_5
Proposed approach	4	1	5	3	2
Traditional TODIM	5	1	4	3	2
Ordinary PIVHF-TODIM	4	1	5	3	2
VIKOR	4	1	5	3	2
TOPSIS	3	1	5	4	2
PROMETHEE	4	1	5	3	2

Fig 13. Comparison of ranking results

V. Conclusion

This paper investigates the comprehensive assessment of the GD potential of the RG considering the influence of socio-physical attributes. It constructs a comprehensive assessment index system for green development, incorporating 15 indicators across three dimensions: energy-physical, economic-technical, and human-social aspects. A PIVHFE distance measure and score function conforming to the theorem constraint is designed. Building on this, the study proposes the PIVHF-TODIM method, which accounts for the subjectivity and uncertainty inherent in perceiving green development potential. Drawing upon the case study evidence, we derive the following conclusions:

(a) This paper begins by examining the driving factors of GD in regional power grids, considering the influence of social and physical factors. We construct an index system for the GD potential of RGs, providing a theoretical basis for understanding this potential.

(b) The PIVHF-TODIM method is proposed to assess the GD potential of regional power grids. The method employs an improved entropy weighting approach under a probabilistic interval-valued hesitant fuzzy environment for indicator weighting. Furthermore, a novel distance measure and score function are constructed based on the deviation of PIVHFEs from their mean values. The proposed distance measure and score function substantially improve the TODIM method's effectiveness in evaluating regional power grids' green development potential.

(c) The proposed method was implemented in Shanghai's newly developed urban areas. The implementation results demonstrate the method's feasibility and effectiveness.

In addition, the proposed hybrid methodology, which integrates hesitant fuzzy elements with the TIDOM framework, offers an effective solution for complex decision-making processes while reducing information loss. The proposed approach establishes a comprehensive theoretical foundation for perceiving the GD potential within RGs.

References

[1] B. W. Yi, J. H. Xu and Y. Fan, "Coordination of Policy Goals Between Renewable Portfolio Standards and Carbon Caps: A Quantitative Assessment in China," Applied Energy, vol. 237, pp. 237: 25-35, 2019.

[2] X. Li, and S. Niu, "Study on multi-layer evaluation system of source-grid-load under carbon-neutral goal," Proc Chin Soc Electrical Eng, vol. 41, 2021.

[3] H. L. Wu, E. Du, and K. Men, "A Low-Carbon Oriented Energy-Saving and Economic Operation Evaluation System," Power System Technology, vol. 39, no. 5, pp. 1179-1185, 2015.

[4] Z. Li, and Y. Wang, "Construction and Application of Low Carbon Power Grid Benefit Evaluation Model in New Power System," Lamps & Lighting, vol. 1, pp. 198-200, 2023.

[5] Y. L. Sun, C. G. Kang, and S. S. Chen, "Low carbon power grid evaluation index system and method," Automation of Electric Power Systems, vol. 38, pp. 157-162, 2023.

[6] P. L. Du, X. M. Gong, B. Han, and X. Zhao, "Carbon-neutral Potential Analysis of Urban Power Grid: A Multi-stage Decision Model based on RF-DEMATEL and RF-MARCOS," Expert Systems with Applications, vol.234, pp. 121026, 2023.

[7] S. Y. Xiang, Z. X. Cai, P. Liu, and L. C. Li," Fuzzy Comprehensive Evaluation of the Low-carbon Operation of Distribution Network Based on AHP-Anti-Entropy Method," Journal of Electric Power Science and Technology, vol. 34, no.4, pp. 69-76, 2019.

[8] N. Liu, X. H. Yu, J. H. Wang, and Y. S. Xue, "Optimal Operation of Power Distribution and Consumption System Based on Ubiquitous Internet of Things: A Cyber-Physical-Social System Perspective," Automation of Electric Power Systems, vol. 44, no.1, pp. 1-12, 2020.

[9] X. Q. Han, T. J. Li, D. X. Zhang, and X. Zhou, "New Issues and Key Technologies of New Power System Planning Under Double Carbon Goals," High Voltage Engineering, vol. 47, no.9, pp. 3036-3046, 2021.

[10] D. L. Gao, X. F. Yu, and H. B. Du, "Research on Evaluation of Decision-making Ability for Fire Commander of Civil Airport based on Cloud Model," Journal of Safety Science and Technology, vol. 14, no.4, pp. 57-62, 2018.

[11] J. W. Gao, X. Huang, F. J. Guo, and X. Z. Li, "Probabilistic Hesitant Fuzzy Multi-Criteria Decision-making Method Based on Cumulative Prospect Theory," Mathematics in Practice and Theory, vol. 51, no.10, pp. 45-58, 2021.

[12] V. Torra, "Hesitant Fuzzy sets," International Journal of Intelligent Systems, vol. 25, pp. 529-539, 2010.

[13] Z. M. Zhang, and C. Wu, "Weighted Hesitant Fuzzy Sets and Their Application to Multi-criteria Decision Making," British Journal of Mathematics & Computer Science, vol. 4, no. 8, pp. 1091-1123, 2014.

[14] X. L. Zhou, and Q. G. Ma, "Probabilistic Hesitant Fuzzy Algorithm and Its Application for Selection Method of Network Public Opinion Prediction Model," Computer Engineering and Applications, vol. 55, no.4, pp. 179-184, 2019.

[15] R. Q. Fan, Y. Yang, K. Xu, and W. T. Xu, "A Review of Typical Characteristics and Development Challenges of New Power System Considering 'Dual Carbon' Goal," Sichuan Electric Power Technology, vol. 46, no.6, pp. 10-14, 2023.

[16] F. Wang, B. Zhou, and H. Zhang, "Generation-Grid-Load-Storage Coordination and Interaction Assists Construction of New Power

System Under the Background of ‘Double Carbon’,” China Resources Comprehensive Utilization, vol. 40, no. 5, pp. 188-191, 2022.
[17] P. Ren, W. H. Niu, P. Li, and Y. R. Zhang, “Calculation Method for Capacity Load Ratio of AC Grid at Multiple Voltage Levels,” Journal of Power Supply, vol. 22, no. 6, pp.170-178, 2022.
[18] P. Chinnasamy, N. Palanichamy, K. Wong, K. D. Michael, and I. Jayaraman, “Energy Efficiency Enhancement of Fossil-Fuelled Power Systems,” International Journal of Energy Economics and Policy, vol. 5, no. 3, pp. 765-771, 2015.
[19] I. Sotnyk, T. Kurbatova, Y. Romaniuk, O. Prokopenko, and V. Gonchar, “Determining the Optimal Directions of Investment in Regional Renewable Energy Development,” Energies, vol. 15, no. 10, pp. 3646, 2022.
[20] Y. H. Zhang, and T. Zhang “Urbanization, Technological Innovation and Carbon Emission Since the Reform and Opening Up,” Forum on Science and Technology in China, vol. 4, pp. 28-34, 2019.
[21] B. Fang, B. Han, and C. H. Wen, “Probabilistic Hesitant Fuzzy Multi-Attribute Group Decision-making Based on New Distance Measure,” *Control and Decision*, vol. 37, no.3, pp. 729-736, 2022.
[22] Y. Y. Liang, “Selection of Data Products Based on Probabilistic Hesitant Fuzzy Information Aggregation Algorithm,” Computer Engineering and Applications, vol. 55, no.3, pp. 219-224, 2019.
[23] Y. Zhu, D. C. Li, and Q. N. Guo, “Distance Type Probabilistic Interval-valued Hesitation Fuzzy Entropy and Its Decision Application,” Journal of Shanxi University, vol. 47, no. 6, pp. 1178-1189, 2024.
[24] Z. W. Wu and W. Zhang, “Improved Entropy Method and Its Application in Crane Safety Evaluation,” *Machine Design and Research*, vol. 38, no.1, pp. 207-210, 2022.
[25] X. Y. Feng, and S. J. Qu, “Multi-attribute Emergency Location Decision Based on Maximum Deviation Method and TODIM Method in Fuzzy Environment,” Mathematics in Practice and Theory, vol. 52, no.1, pp. 103-118, 2022.
[26] E. S. Du, Y. L. Sun, and N. Zhang, et al, “Transmission Expansion Planning Model Facilitating Low-Carbon Power Sources’ Development,” Power System Technology, vol. 39, no.10, pp. 2725-2730, 2015.
[27] X. Gong, J. Zhang, X. Zhao, “A BWM-TODIM based Integrated Decision Framework for Financial Technology Selection with Interval Type-2 Fuzzy Sets,” IAENG International Journal of Applied Mathematics, vol.52, no. 4, pp. 826-837, 2022.

Yi Zhang, male, born in November 1979, Associate Professor, earned a Bachelor of Engineering degree in July 2001, majoring in Electrical Engineering and Automation from the Department of Electrical Engineering at Shanghai University of Electric Power, China; obtained a Master's degree in Management Science and Engineering from the School of Economics and Management at Tongji University, China in March 2010; Currently, Zhang is pursuing a Ph.D. in Management Science and Engineering at the School of Economics and Management, Tongji University, China.

Since June 2011, he has held various positions at Shanghai University of Electric Power, including Deputy Director of the Party Committee's Student Affairs Office, Vice Dean of the School of Economics and Management, and Party Committee Secretary (Pudong New District, Shanghai, China). From August 2022 to October 2023, he was seconded to the East China Regulatory Bureau of the National Energy Administration, serving as Deputy Director (at the director level) of the Industry Regulation Division. He has published over 20 papers as the first author in prominent domestic and international academic journals (including 12 SCI/EI/CSSCI-indexed papers). He has been granted 4 invention patents and has authored 3 textbooks. He has been awarded the Shanghai Educating Talent Prize, as well as one first prize and one second prize in the Shanghai Outstanding Teaching Achievement Awards.