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Risk assessment method of power communication network based on gray cloud theory and matter-element extension model coupling

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ABSTRACT The failure of the power communication network often leads to a cascading failure of the power system. Evaluating the potential risks in the power communication network is crucial to ensure the stable operation of the power system. This paper proposes a comprehensive risk assessment method for qualitative and quantitative measures. Firstly, an index system for risk assessment, considering both static structure and dynamic operation, is established. The optimal weight of each index is determined using the combination game weighting method. Additionally, a risk assessment model for the power communication network is established by coupling gray cloud theory and matter-element extension model. The fuzzy theory's triangular modulus operator is utilized to fuse three types of fault probabilities, quantify the risk value of the power communication network, and assign it a grade. Finally, experimental results demonstrate that this method improves discrimination degree by 1.2%, 92%, and 85% respectively compared to other traditional algorithms.

INDEX TERMS Gray cloud theory, matter-element extension model, triangular modulus operator, comprehensive risk assessment.

I. INTRODUCTION

THE safe and reliable operation of the Power Communication Network (PCN) is crucial for ensuring the stable operation of the power system. Conducting scientific and accurate risk assessments of the power communication network and implementing appropriate management measures are of utmost importance to minimize the occurrence of major power events.

Since the proposal of the risk assessment theory of the power communication network, extensive research has been conducted by relevant researchers. The evaluation methods primarily consist of approaches based on uncertainty analysis theory [1–4],reliability theory [5–9], and artificial intelligence algorithms [10–13]. In recent years, the uncertainty analysis theory-based evaluation method has been widely applied in power quality assessment [14–16], power safety risk assessment[17, 18], power system equipment condition assessment[19–22], and power grid operation risk assessment [23–25]. In reference[1], the risk assessment model of power communication network based on traditional matter-element fails to fully consider the fuzziness and randomness associated with determining the risk for the boundary value or measured value of each index. Reference [26] introduced a risk assessment and grading system for power grid operation, addressing the issues of insufficient response to the details of the risk assessment index system and inadequate risk information. Reference [3] proposed a method for assessing the risk of power communication network using compatible rough-fuzzy sets. This method effectively addressed the fuzzy issue of decision attribute values. Additionally, references [5] and [27] quantified the risk level of power communication network from the perspective of service failure. However, these studies focused solely on operational risks and considered relatively limited risk factors.

This paper aims to assess the risk in the power communication network by considering the probability and consequences of accidents (faults). It takes into account both the static structural risk factors and dynamic operation risk factors. The PCN risk assessment index system is established using the analytic hierarchy process and the entropy weight method to determine the subjective and objective weights of each index. Weight coefficients are assigned using the combined game weighting method. The risk assessment model combines the matter-element extension model, gray theory, and cloud model theory to evaluate the risk level of each indicator and judge the overall severity of risk in the power communication network. The triangular modulus operator in fuzzy theory is used to integrate the failure probability of human factors, equipment factors, and natural factors, resulting in a comprehensive risk occurrence probability. This approach enables qualitative and quantitative risk assessment of the power communication network, providing a basis for decision-making in risk avoidance and management.

II. RISK ASSESSMENT FRAMEWORK AND RISK ASSESSMENT INDEX OF THE POWER COMMUNICATION NETWORK

A. RISK ASSESSMENT FRAMEWORK OF THE POWER COMMUNICATION NETWORK

This paper presents a risk assessment method for the power communication network by combining gray cloud theory and matter-element extension model. The overall research framework is illustrated in Figure 1 and comprises three main parts: the development of a risk assessment index system, the investigation of a risk assessment method, and the study of risk occurrence probability.

In this study, we first analyze the risk factors of the power communication network by considering its static structure and dynamic operation. Based on this analysis, we construct a risk assessment index system for the power communication network. To determine the subjective and objective weights of each index, we employ the analytic hierarchy process and entropy weight method. The weight coefficients are then distributed using the combination game weighting method, allowing us to obtain the optimal weight coefficient for each index.The second part of our research focuses on developing a risk assessment method for the power communication network. We propose a model that combines the matter-element extension model, gray theory, and cloud model theory to leverage the advantages of each. The matter-element extension model enables us to perform qualitative and quantitative analysis, while the clustering evaluation method based on gray theory provides the evaluation cloud level for each index and allows us to assess the overall risk severity of the power communication network. Additionally, the cloud model theory takes into account the randomness and fuzziness of the power communication network's operation state.The third part discusses the study of the probability of risk in the context of power communication network. It explains that the probability function of comprehensive risk occurrence is established using the triangular modulus operator in fuzzy theory. This function fuses the fault probability of human factors, equipment factors, and natural factors. The risk classification and risk quantification of the power communication network are achieved through the research conducted on the three aforementioned aspects. This research enables the acquisition of qualitative and quantitative comprehensive evaluation results.

B. CONSTRUCTION OF RISK ASSESSMENT INDEX SYSTEM

The paper establishes a risk assessment index system for the power communication network based on its static structure[28–31] and dynamic operation [32–34].

1) Static structural risk factors

The static structural risk factors of the network mainly focus on the attributes of communication network nodes and the connectivity of the entire network. These factors include the location, load level, and size of communication nodes, as well as the importance of each unit in the network topology.

2) Dynamic operation risk factors

The dynamic operational risk of a power communication network primarily focuses on the quality of facility operation, business operation, and network resource scheduling. This includes factors such as the probability of failure, rate of defect elimination, resource utilization, and service transmission reliability.

The risk of a power communication network encompasses both the static structural risk and the dynamic operational risk. Building upon the analysis of risk factors mentioned earlier, this paper proposes a risk assessment index system for the 'static structure-dynamic operation' power communication network, as depicted in Figure 2.

The subjective weight and objective weight of each index are calculated using the analytic hierarchy process and the entropy weight method, respectively. The weight coefficient is then distributed using the combination game weighting method to determine the comprehensive weight value of each evaluation index.

The calculation steps of entropy weight method are as follows:

1. Form the evaluation matrix $R^{'}$

$$R^{'} = \begin{bmatrix} r^{'}_{11} & \cdots & r^{'}_{1m} \\ \vdots & r^{'}_{ij} & \vdots \\ r^{'}_{n1} & \cdots & r^{'}_{nm} \end{bmatrix} \tag{1}$$

where r'_{ij} represents the actual data of the ith node under the jth indicator. $i = 1, 2, \cdots, n, j = 1, 2, \cdots, m$. n is the number of nodes, m is the number of evaluation indexes.

2. Calculate the proportion of the ith node under the jth index P_{ij}

$$P_{ij} = r'_{ij} / \sum_{i=1}^{n} r'_{ij} \tag{2}$$

3. Calculate the entropy value of the evaluation indicators

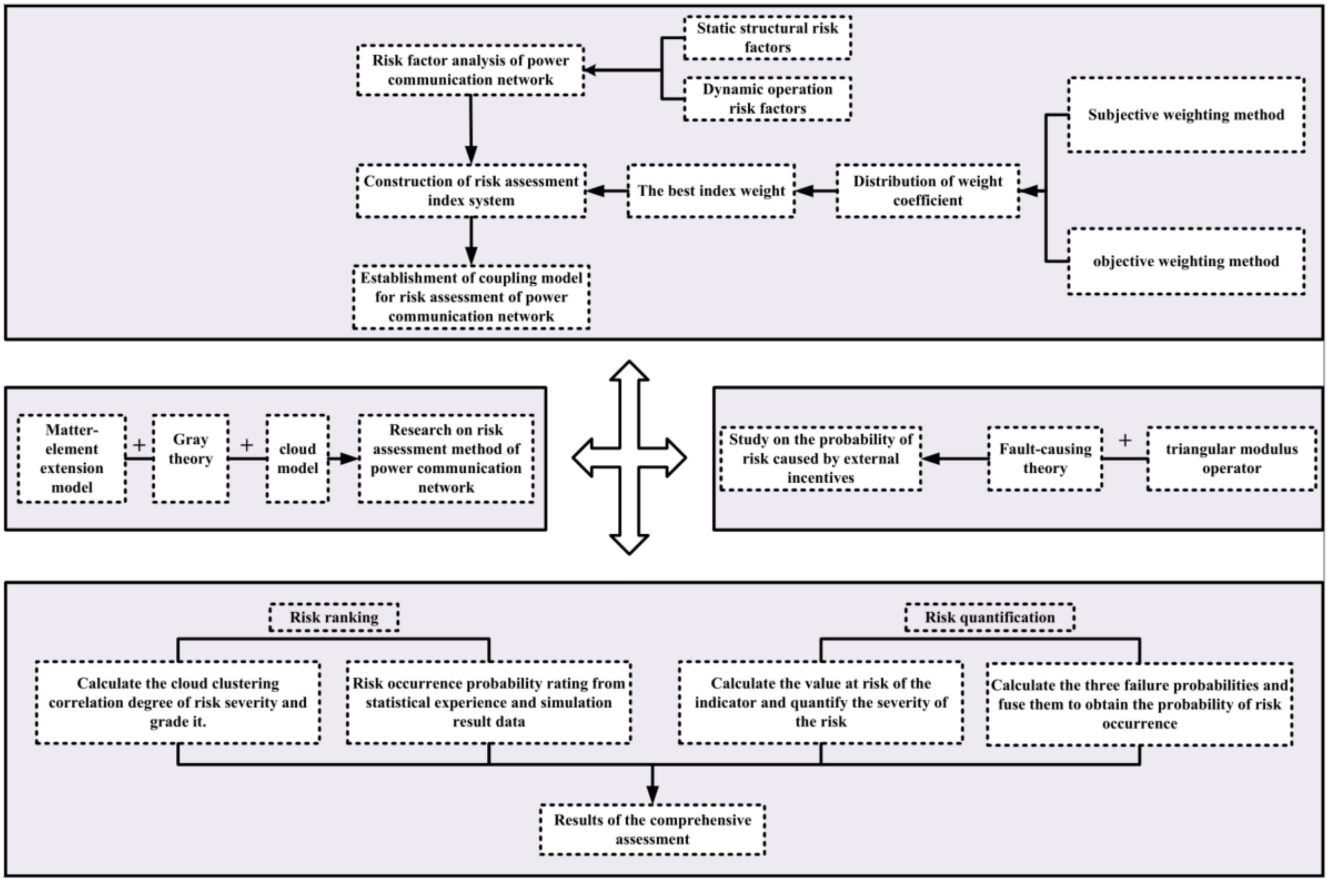


FIGURE 1. The overall research framework of this paper.

$$e_j = k \sum_{i=1}^{n} P_{ij} \ln P_{ij} \tag{3}$$

In the formula, $k = -\frac{1}{\ln N}$.

Then the weight of the jth indicator is calculated by the formula:

$$w_j = \frac{1 - e_j}{\sum_{i=1}^{n} (1 - e_j)} \tag{4}$$

The calculation steps of analytic hierarchy process method are as follows:

1. Constructing comparison matrix R

$$R = (r_{ij})_{n \times m} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & r_{ij} & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \tag{5}$$

2. Consistency test of the matrix

The consistency indicator is defined as :

$$CI = \frac{\lambda_{\max} - n_r}{n_r - 1} \tag{6}$$

In the formula, n_r is the order of the matrix, and $\lambda_{\max}$ is the maximum eigenvalue corresponding to the matrix.

Introduce random consistency index RI:

$$RI = \frac{CI_1 + CI_2 + \cdots + CI_{nr}}{n_r} \tag{7}$$

Calculate the consistency check coefficient CR:

$$CR = \frac{CI}{RI} \tag{8}$$

Usually, if $CR<0.1$, the matrix is considered to pass the consistency test, and the maximum eigenvalue vector of the matrix is the obtained weight vector.

The weight vector calculated by the analytic hierarchy process and the entropy weight method is:

$$w_f = \left(w_{f1}, w_{f2}, \cdots, w_{fm} \right), \left(f = 1, 2 \right). \tag{9}$$

In the formula, m is the number of indexes. f=1 indicates the use of analytic hierarchy process to calculate weights, f=2 indicates that the entropy weight method is used to calculate the weights.

Optimize the weight coefficient:

$$\min \|\alpha_1 w_1 + \alpha_2 w_2 - w_1 - w_2\|_2 \\ s.t. \begin{cases} \alpha_1 + \alpha_2 = 1 \\ 0 \le \alpha_1 \le 1 \\ 0 \le \alpha_2 \le 1 \end{cases} \tag{10}$$

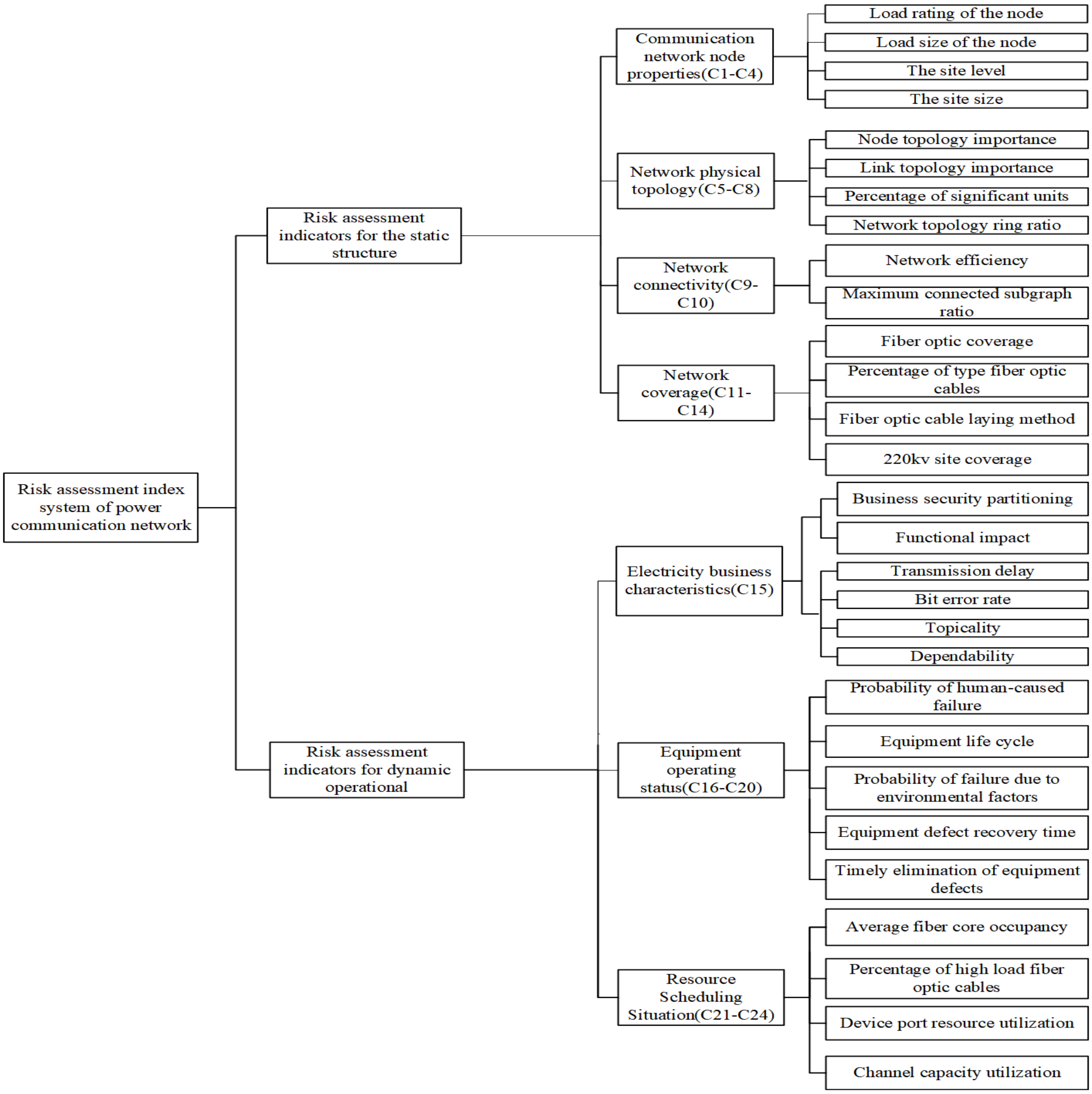


FIGURE 2. Risk assessment index system of power communication network.

According to the differential properties of matrices, the first derivative of (10) can be transformed into

$$\begin{bmatrix} w_1 w_1^T & w_1 w_2^T \\ w_2 w_1^T & w_2 w_2^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} w_1 w_1^T \\ w_2 w_2^T \end{bmatrix} \tag{11}$$

The optimal weight obtained by the combination game weighting method is:

$$w = \alpha_1 w_1 + \alpha_2 w_2 \tag{12}$$

In the formula, w_1 and w_2 are the weight vectors obtained by the two weighting methods, $alpha_1$ and $alpha_2$ are the corresponding weight coefficients. w is the final optimal weight vector.

III. RISK COUPLING EVALUATION MODEL OF POWER COMMUNICATION NETWORK

This section provides a comprehensive evaluation of the risk of power communication network, considering the severity of risk consequences and the probability of risk occurrence. The assessment is based on the relevant data provided by a specific area in Jilin Province, which determines the value of each risk assessment index.

A. RISK CONSEQUENCE SEVERITY QUANTIFICATION AND GRADE ASSESSMENT

1) Quantitative mathematical model of risk consequence severity

Let Q be the quantitative value of risk severity. According to the index system of " static structure-dynamic operation, " q_1 is the influence value of static structure of communication network, and q_2 is the influence value of dynamic operation. Then:

$$\begin{aligned} Q &= q_1 + q_2 \\ &= \sum_{j=1}^{m_1} w_j F\left(U_j\right) + \sum_{j=m_1}^{m} w_j F\left(U_j\right) \end{aligned} \tag{13}$$

In the formula, $F(U_j)$ represents the value of each evaluation index, w_j is the weight of index j , $j = 1, 2, \cdots, m$. . For cost-based indicators, $F(U_j)$ is the sum of the risk values of each indicator. For the benefit index, the deviation of the index is used to measure the risk value of the index. The calculation function of $F(U_j)$ is:

$$F\left(U_j\right) = \sum_{z=1}^{N_n} \frac{e^{\max\left(\frac{V_j - \bar{V}_j}{\bar{V}_j}, \frac{\underline{V}_j - V_j}{\underline{V}_j}, 0\right)} - 1}{e - 1} \tag{14}$$

In the formula, N_n is the total number of unit nodes in the network, V_j is the value of the node under the index j , $\bar{V}_j$ and $\underline{V}_j$ are the upper and lower limits of the node Z under the index j measure, respectively.

2) Grading mathematical model of risk consequence severity

The matter-element theory in topology provides a qualitative and quantitative description of the development and change of things. The cloud model is an effective model that integrates the randomness and fuzziness of information and enables the transformation of uncertainty between qualitative concepts and quantitative values. Therefore, this paper proposes to enhance the traditional gray clustering whitening weight function by utilizing the cloud model. It also aims to establish a risk assessment model for power communication network by combining the gray cloud theory and matter-element extension model.

1. Define matter element

In the formula, R_s is the level of PCN risk consequence evaluation, N represents the risk of power communication network, $C = \{C_1, C_2, \cdots, C_m\}$ represents the set of risk indicators, and $V = \{V_1, V_2, \cdots, V_m\}$ represents the quantitative value of risk indicators. $V_{sj} = (L_{sj}, R_{sj})$ is the value range of index j under grade $s, j = 1, 2, \cdots, m, s = 1, 2, 3, 4$. According to expert opinions, the classification scheme of qualitative index is determined. Additionally, the specific value of a certain period of indicators is divided into intervals to establish the grading scheme for quantitative indicators. Referring to the historical data of the provincial power grid companies and literature , this paper designs the index grading scheme for the qualitative index as shown in table 1.

$$R_s = (N, C, V) = \begin{pmatrix} N & C_1 & V_1 \\ & C_2 & V_2 \\ & \vdots & \vdots \\ & C_m & V_m \end{pmatrix} = \begin{pmatrix} N & C_1 & (L_{s1}, R_{s1}) \\ & C_2 & (L_{s2}, R_{s2}) \\ & \vdots & \vdots \\ & C_m & (L_{sm}, R_{sm}) \end{pmatrix} \tag{15}$$

2. Cloud description of hierarchical boundaries

The left and right boundary values of the evaluation index classification are used as a double constraint space $\left[L_x, R_x\right]$. The digital characteristics of the gray cloud model include:

$$\begin{aligned} E_x &= \frac{L_x + R_x}{2} \\ E_n &= \frac{R_x - L_x}{6} \\ H_e &= \frac{E_n}{p} \end{aligned} \tag{16}$$

Where p is a given constant. By formula (16), the traditional matter-element extension model of formula (15) is transformed into:

$$R_s = (N, C, V) = \begin{pmatrix} N & C_1 & (E_{x1}, E_{n1}, H_{e1}) \\ & C_2 & (E_{x2}, E_{n2}, H_{e2}) \\ & \vdots & \vdots \\ & C_m & (E_{xm}, E_{nm}, H_{em}) \end{pmatrix} \tag{17}$$

Replace V with the digital eigenvalue (E_{xj}, E_{nj}, H_{ej}) of the gray cloud model, (E_{xj}, E_{nj}, H_{ej}) is the cloud description of the evaluation index C_j about the grade $R_s, j = 1, 2, \cdots, m$. This modification addresses the limitation of the traditional matter-element extension model, which overlooks the complete consideration of the randomness and fuzziness associated with the state level boundary during the division of the index interval.

3. Cloud model improves the traditional whitening weight function

The index value x to be evaluated is regarded as a cloud droplet, and a random number $E_n^{'}$ obeying normal distribution with an expected value of E_n and a standard deviation of H_e is generated. The function form of the expected membership whitening value, calculated by the gray cloud whitening weight function, is improved by introducing the cloud model.

$$f\left(x\right) = \exp\left(-\frac{\left(x - E_x\right)^2}{2\left(E_n^{'}\right)^2}\right), x \in \left[L_x, R_x\right] \tag{18}$$

The expression of the whitening weight function is divided into three categories. If the whitening weight function of the index j on the kth grade is:

$$f_j^k\left(x\right) = \begin{cases} \exp\left(-\frac{(x - E_x)^2}{2\left(E_n^{'}\right)^2}\right), x \in \left[L_x, R_x\right] \\ 0, x \notin \left[L_x, R_x\right] \end{cases} \tag{19}$$

It is called the moderate measure normal gray cloud model, denoted by $\left[E_{xj}^k, E_{nj}^k, H_{ej}^k\right]$.

If the whitening weight function of index j with respect to the kth grade satisfies

$$f_j^k\left(x\right) = \begin{cases} 1, x \in \left[L_x, E_x\right] \\ \exp\left(-\frac{(x - E_x)^2}{2\left(E_n^{'}\right)^2}\right), x \in \left[E_x, R_x\right] \\ 0, x \notin \left[L_x, R_x\right] \end{cases} \tag{20}$$

TABLE 1. Grading scheme of qualitative evaluation index

Qualitative indicators	Grade1	Grade2	Grade3	Grade4
Site level	500KV plant station, center transfer	220kv plant station, ground control	110kv and below plant station, county transfer	Enterprise internal management, office
Site size	Hub	Regional station	Terminal	–
Load rating	Premium Users	Level 1 critical users	Level 2 critical users	Temporary critical users
Load size	40% and above	16% to 40%	12% to 16%	6% to 12%
Delay	$\leqslant$ 10ms	$\leqslant$ 150ms	$\leqslant$ 1s	Not demanding
Bit error rate	$\leqslant 10^{-9}$	$\leqslant 10^{-7}$	$\leqslant 10^{-5}$	$\leqslant 10^{-3}$
Security partition	Partition 1	Partition 2	Partition 3	Partition 4

It is called the lower limit measure normal gray cloud model, denoted by $\left[-;\left(E_{xj}^k, E_{nj}^k, H_{ej}^k\right)\right]$. If the whitening weight function of index j with respect to the kth grade satisfies

$$f_j^k(x)=\begin{cases}\exp\left(-\frac{(x-E_x)^2}{2\left(E_n'\right)^2}\right), x\in[L_x,E_x]\\ \\ 1, x\in[E_x,R_x]\\ 0, x\notin[L_x,R_x]\end{cases} \tag{21}$$

It is called the upper limit measure normal gray cloud model, denoted by $\left[\left(E_{xj}^k, E_{nj}^k, H_{ej}^k\right);-\right]$ .In the evaluation process, the nature of the index is divided into two types: benefit type and cost type, and the corresponding whitening weight function type is selected according to the quantitative change characteristics of the index.This improvement addresses the shortcomings of the conventional gray clustering method, which fails to distinguish the characteristics of various types of indicators.

4. Calculating the correlation degree of cloud clustering

The average value $f_j'^k(x)$ of p times calculated by the whitening weight of index j with respect to gray class k is

$$\begin{aligned}f_j'^k(x)&=\frac{1}{p}\sum_{t=1}^{p}f_{jt}^k(x)\\&=\frac{1}{p}\left(f_{j1}^k(x)+f_{j2}^k(x)+\cdots+f_{jp}^k(x)\right)\end{aligned} \tag{22}$$

In the formula, $f_{jt}^k(x)$ is the value of the whitening weight function calculated at the tth time, $t\in[1,p]$. The whitening weight function value for each evaluation grade describes the degree of cloud clustering correlation of the quantitative value of the index. The whitening weights of the same index at different grades are normalized.

$$\tau_j^k(x)=\frac{f_j^k(x)}{\sum_{k=1}^{s}f_j^k(x)} \tag{23}$$

where s is the number of grades, $k=1,2,\cdots,s$.

5. Determine the grade of risk severity

The calculation of the cloud clustering correlation between each index value and the evaluation grade is weighted as follows:

$$\lambda^k=\sum_{j=1}^{m}\tau_j^k(x)w_j \tag{24}$$

In the formula, $\tau_j^k(x)$ is the normalized whitening weight, which is the weight of w_j index $j, j=1,2,\cdots,m$. The cloud clustering correlation vector under the current operating state of the power communication network is

$$\begin{aligned}\lambda_i^k&=\left(\lambda_i^1,\lambda_i^2,\cdots,\lambda_i^s\right)\\&=\left(\sum_{j=1}^{m}\tau_j^1(x)\bullet w_j,\sum_{j=1}^{m}\tau_j^2(x)\bullet w_j,\cdots,\sum_{j=1}^{m}\tau_j^s(x)\bullet w_j\right)\end{aligned} \tag{25}$$

The value k of the risk severity level R_s is determined according to $\lambda_i^k=\max\left(\lambda_i^1,\lambda_i^2,\cdots,\lambda_i^s\right), k=1,2,\cdots,s.$

6. Test the evaluation results of PCN

To mitigate the impact of randomness in calculating the cloud clustering correlation degree between the index value and the normal gray cloud, this study conducts multiple calculations and determines the expected value and entropy of the evaluation results using the following formula:

$$\begin{aligned}E_{\lambda x}&=\frac{\lambda(x_1)+\lambda(x_2)+\cdots+\lambda(x_H)}{H}\\E_{\lambda n}&=\sqrt{\frac{1}{H}\sum_{h=1}^{H}\left(\lambda(x_h)-E_{\lambda x}\right)}\end{aligned} \tag{26}$$

In the formula, $E_{\lambda x}$ and $E_{\lambda n}$ are the expected value and entropy of the evaluation results, respectively. The H value is taken 100 times in this paper, and $\lambda(x_h)$ is the evaluation result obtained by the hth operation. The expected value represents the average level of the evaluation results, while entropy measures the dispersion of the evaluation results. A larger entropy value indicates more dispersed evaluation results. Therefore, the credibility factor δ is defined as:

$$\delta=\frac{E_{\lambda x}}{E_{\lambda n}} \tag{27}$$

The greater the value of δ , the greater the dispersion of the evaluation results, the smaller the credibility of the evaluation results. On the contrary, the greater the credibility of the evaluation results.

B. RISK OCCURRENCE PROBABILITY AND GRADE EVALUATION

Referring to the standard GB/T 38438-2019 'Operation Evaluation Index System of Power Communication Network' and GB/T 40585-2021 'Technical Specification for Monitoring, Evaluation and Visualization of Power Grid Operation Risk', this study categorizes fault causes into human factors, equipment factors, and natural factors, based on the theory of fault cause analysis. Among them, human factors mainly refer to line failures and machine malfunctions caused by random events such as personnel building construction and personnel misuse. The entire service period of the equipment can be divided into three phases: the initial failure period, incidental failure period, and wear and tear period. The early failure period is primarily caused by issues such as product process and equipment quality. To prevent early failures, substandard products are identified and removed through screening. During the incidental failure period, equipment operates stably with a low failure rate. However, as equipment ages and experiences wear and tear, its performance gradually deteriorates, leading to an increase in failure rate. This phase is known as the wear and tear failure period. In practice, equipment is replaced with new ones when it reaches a certain age to avoid such failures. Therefore, this paper primarily focuses on studying the more common incidental failure period throughout the equipment's service period. On the other hand, natural factors mainly refer to tower collapse and line breakage caused by severe external disasters such as wind, rainstorms, lightning strikes, and ice cover. Accordingly, this paper proposes calculation methods for the failure probability of human factors based on the Poisson distribution, the failure probability of equipment factors based on the Markov process, and the failure probability of natural factors based on historical statistics.

A counting process is a stochastic process $\{\mathrm{N(t), t} \geqslant 0\}$ that represents the total number of events that have occurred up to time t. It is considered to have independent increments if the number of events occurring in disjoint time intervals are independent of each other. Additionally, the counting process is said to have smooth increments if the distribution of the number of events occurring in any time interval depends solely on the length of the time interval. In literature [35], it has been confirmed that the probabilistic prediction method based on the Poisson distribution is effective for risk assessment of transmission line tripping.According to the Poisson theorem, the Poisson distribution is applicable for describing the occurrence of rare events. In the context of lines stretching hundreds of kilometers, man-made disasters are considered to be infrequent and independent events. Hence, this paper utilizes the Poisson distribution to model the probability of their occurrence within a specific time period, typically one year.

Assuming that the number of failure events due to man-made construction and other reasons is n, the average annual probability of risk disasters in the region can be expressed as

$$P(X=n)=\frac{\theta^n}{n!}e^{-\theta}, n=1,2,\cdots \tag{28}$$

The probability of at least one risk disaster in a year is

$$P(X\geq 1)=1-e^{-\theta}, n=1,2,\cdots \tag{29}$$

In the formula, the maximum likelihood estimate of the parameter θ is determined using the maximum likelihood estimation method [35]. The expression for this estimate is:

$$\hat{\theta}=\frac{\sum_{v=1}^{l} x_v}{l} \tag{30}$$

In the formula, x_v is the sample observation value of l lines, $\nu=1,2,\cdots,l$.

In the on-line risk assessment, the equipment is time-varying outage, so this paper simulates the equipment failure probability using a Markov process model based on time continuous and state discrete, and uses the Fokker-Planck equation to solve . Here, the state space is simplified to three states, including: 0 state (normal operation), 1 state (instantaneous fault), and N state (permanent fault). The corresponding Fokker-Planck equation is as follows:

$$\begin{bmatrix} P_0'(t) \\ P_1'(t) \\ P_N'(t) \end{bmatrix} = \begin{bmatrix} -(\gamma_{0\to 1}+\gamma_{0\to N}) & \mu_{1\to 0} & \mu_{N\to 0} \\ \gamma_{0\to 1} & -\mu_{1\to 0} & 0 \\ \gamma_{0\to N} & 0 & -\mu_{N\to 0} \end{bmatrix} \begin{bmatrix} P_0(t) \\ P_1(t) \\ P_N(t) \end{bmatrix} \tag{31}$$

In the formula, $P_i(t)$ is the instantaneous probability under the state i at time t , $i = 0,1,N$.$\gamma_{0\to 1}$ and $\gamma_{0\to N}$ are the transfer rate from the running state to the instantaneous fault state and the permanent fault state respectively, $\mu_{1\to 0}$ and $\mu_{N\to 0}$ are the transfer rate from the instantaneous fault state and the permanent fault state to the running state respectively, that is, the repair rate.

The eigenvalue of the system of differential equations obtained by the above formula is a real number [26], and the form of its solution is

$$\begin{cases} P_0(t)=a_0+b_0e^{x_1 t}+c_0e^{x_2 t} \\ P_1(t)=a_1+b_1e^{x_1 t}+c_1e^{x_2 t} \\ P_N(t)=a_N+b_Ne^{x_1 t}+c_Ne^{x_2 t} \end{cases} \tag{32}$$

The parameters a_i, b_i, c_i, x_j in the formula are calculated by the transfer rate $\gamma_{0\to i}$, $\mu_{i\to 0}$ and the probability distribution $\left[P_0^0, P_1^0, P_N^0\right]$ of the initial time of each state. i=0,1,N; j=1,2.

This study focuses on various natural factors, including wind, rainfall, lightning, icing, and other external disaster events, which can vary across different regions. To determine the failure probability of these natural factors, a targeted approach is adopted using regional historical statistical data.

Then T is called a triangular norm operator.Triangular modulus is defined as [25] : if the mapping T:$[0,1]^2 \to [0,1]$,for $\forall a,b,c,d \in [0,1]$, satisfies 1) $T(0,0) = 0, T(1,1) = 1$; 2) if $a \leq c, b \leq d$ then $T(a,b) \leq T(c,d)$; 3) $T(a,b)=T(b,a)$; 4) $T\left(T(a,b),c\right)=T\left(a,T(b,c)\right)$.

For the fault probability to be fused, the triangular modulus operator can meet its requirements. By the following formula

$$T(a,b)=\frac{a\bullet b}{1+(1-a)(1-b)} \tag{33}$$

The three fault probabilities are fused to obtain a comprehensive risk probability I.

In the design of the method presented in this paper, the idea of reference [36] is used as a reference. The fusion failure

TABLE 2. Risk grading scheme

The level of risk		The level of risk probability			
		Grade1	Grade2	Grade3	Grade4
The level of risk severity	Grade1	Grade1	Grade1	Grade2	Grade2
	Grade2	Grade2	Grade2	Grade2	Grade3
	Grade3	Grade2	Grade3	Grade3	Grade3
	Grade4	Grade3	Grade3	Grade4	Grade4

probability result calculated by Equation (33) is used to determine the risk occurrence probability level, which is divided into four levels. Level 1 has a risk occurrence probability per hour above 10^{-4} , level 2 has a risk occurrence probability per hour between 10^{-5}-10^{-4}, level 3 has a risk occurrence probability per hour between 10^{-6}-10^{-5} , and level 4 has a risk occurrence probability per hour above 10^{-7}-10^{-6}.

C. RISK QUANTIFICATION VALUE AND RISK GRADING OF POWER COMMUNICATION NETWORK

Based on the obtained risk consequence value and the comprehensive risk occurrence probability, the expression of the comprehensive quantitative value of the risk assessment of the power communication network is as follows:

$$R = I * Q \tag{34}$$

Based on the risk severity level R_s and the risk occurrence probability level P_s obtained above, the comprehensive risk assessment level of the power communication network is calculated by the following formula:

$$L_s = round\ (\alpha R_s + \beta P_s) \tag{35}$$

In the formula, L_s refers to the risk level,α and β are the weight coefficients with the value interval of $(0, 1)$, $\alpha + \beta = 1$. round() represents rounding. It can be seen from the above formula that if α is 1, it is a traditional deterministic risk assessment method. The evaluation method proposed in this paper takes into account the possibility and consequences of risk occurrence. When $\alpha > \beta$, the risk level result is more inclined to the consequences of risk occurrence. When $\alpha < \beta$, the risk level result is more focused on the possibility of risk occurrence. In various engineering applications, researchers have proposed different forms of risk matrices based on diverse project backgrounds and decision-making attitudes. This paper focuses on the research context of power communication networks, where the classification of risk significance level is influenced by the risk attitude and risk preference of decision makers. It is important to note that there is currently no universally accepted criterion for determining the boundary values that separate probability and severity levels. According to the actual operation of the network, combined with the experience of professionals, considering that power companies generally focus more on the consequences of risk occurrence, set α to 0.6, and get the final risk grading scheme as shown in table 2.

IV. SIMULATION EXPERIMENT

A. EXPERIMENTAL SETTINGS

In this study, we simulate a basic network comprising of 14 nodes and 16 links, and distribute 10 typical conventional services. We refer to the risk analysis research conducted by provincial power grid companies on power communication network (PCN) to evaluate the PCN comprehensively. The evaluation levels of PCN are divided into four categories: serious, abnormal, attention, and good, corresponding to levels 1 to 4. Additionally, we collected 135 sets of fault sample data for analysis.

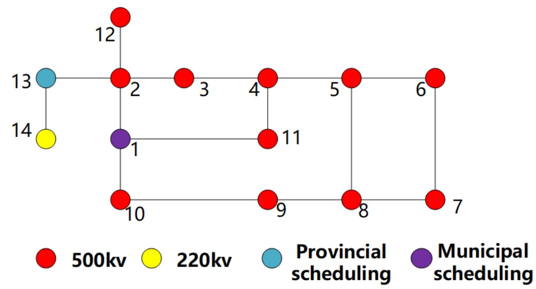


FIGURE 3. Local topology diagram of a region.

B. EXPERIMENTAL RESULT ANALYSIS

1) evaluation result analysis

1. The weight of the established risk assessment index system was calculated.Because the sub-category indicators under the characteristics of electricity business are qualitative indicators, experts are invited to score the six qualitative indicators under the characteristics of electricity business.The sample data of the evaluation index was weighted and combined into an index called C15, which represents the value of electricity business characteristics. Figure 2 shows that there are a total of 24 evaluation indicators, denoted as C1-C24. The weight calculation results for each indicator can be seen in Figure 4.

The entropy weight method is an objective weighting method that calculates the entropy value based on the actual value of each evaluation index. On the other hand, the analytic hierarchy process is a subjective weighting method that relies on expert scoring. The results show significant differences between the two methods when it comes to the ratio index with small actual data. To ensure a balance between the subjective judgment of decision makers and the objective characteristics of evaluation objects, it is advisable to integrate

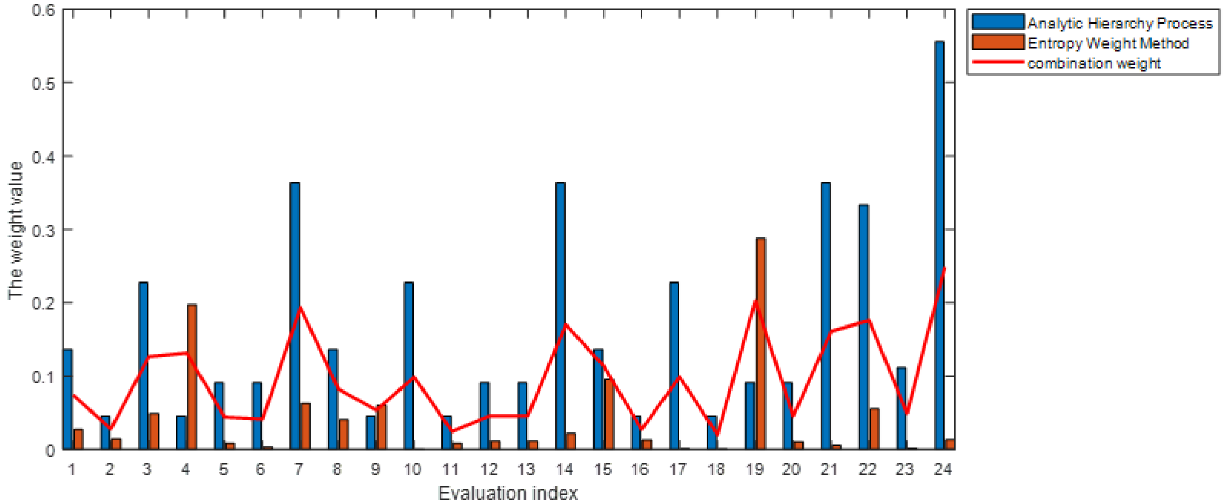


FIGURE 4. **Index weight calculation results.**

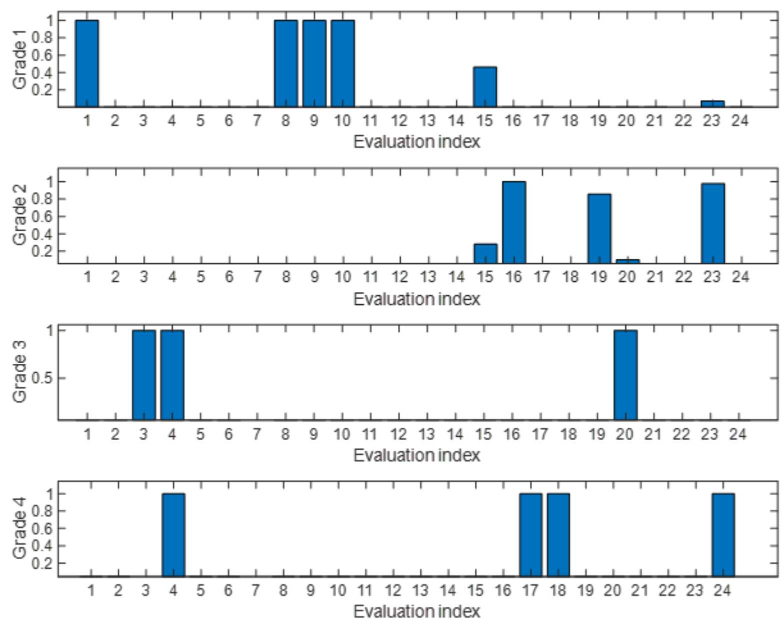


FIGURE 5. **Calculation results of index cloud clustering correlation degree.**

or synthesize the subjective and objective weighting methods in order to obtain more scientifically sound weight results for each evaluation index.The combined game weighting method is used to allocate the weight coefficient, and the obtained comprehensive weight effectively solves the problem that the weight value is too large or too small due to the single weighting method.

2. According to the formula (15) -formula (24), the cloud clustering correlation degree τ_j^k between the risk assessment index and each risk level is obtained, and the results are shown in Figure 5.

Based on the results, the high-risk state indicators include the network topology subclass in the static structure index, the network connectivity subclass, and the power business index in the dynamic operation index. Therefore, managers should focus on these indicators. They should prioritize the load level, as higher importance of service users increases the risk. The network ring rate should also be monitored, as it reflects the network's self-healing ability. Network connectivity indicates the network's invulnerability, and the reliability of transmission power business should be given high attention. Any interruption in transmission business can result in significant losses to the power communication network. Additionally, managers should closely monitor the subcategories of equipment operation status, resource scheduling, and the characteristics of network nodes themselves. These indicators can be managed using conventional management processes.

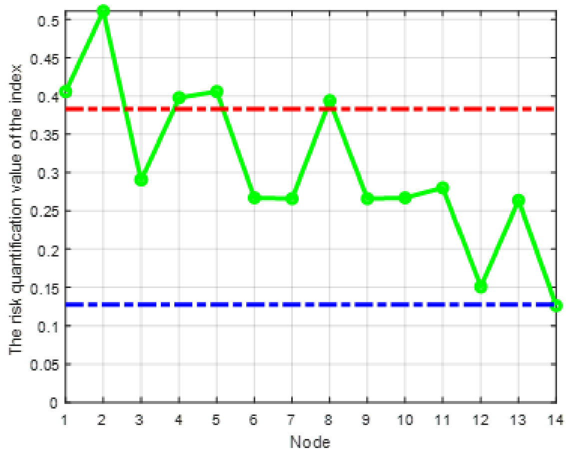
3. Based on the concept of the AIARP criterion for risk classification [37], the risk value is divided into three regions using two risk dividing lines. The red line represents the unacceptable risk level, while the blue line represents the negligible risk level. When considering cost-based indicators, a level 4 risk is identified when the value is less than 25% of the maximum value, while a level 1 risk is associated with a value exceeding 75% of the maximum value. In the case of benefit-based indicators, the degree of deviation from the nominal value is determined using equation (14). A level 4 risk is assigned when the deviation is within 25% of the maximum value, indicating acceptable network operation. Conversely, a level 1 risk is assigned when the deviation exceeds 75% of the maximum value. Figure 6 illustrates the changes in risk quantification values for three selected indicators based on the results shown in Figure 5.

The risk value of the topological structure of each node in the network is presented in Figure a. All node risks are non-negligible, which aligns with the findings in Figure 5. Specifically, the topological index, connectivity index, and risk level 1 exhibit the strongest correlation. Figure b illustrates the business risk value of each node in the network. The results indicate that only node 12 poses low risk, while the remaining nodes pose medium and high risks, consistent with the conclusion of Figure 5. Figure c showcases the risk value of resource scheduling for each node in the network. The findings reveal that only node 14 has high risk, while most nodes operate normally, which is in line with the conclusion of Figure 5, the index has the greatest clustering correlation degree at a good level. It is noteworthy that despite the risk of nodes 5-8 being the same under the C24 index, their risk characteristics differ due to variations in topological connections and business loads. The experimental results validate the comprehensiveness and effectiveness of the established index system. In addition,the final risk value of each node is obtained by summing up the risk values under different index measures. The key nodes of the power communication network can be identified based on the resulting ordering.

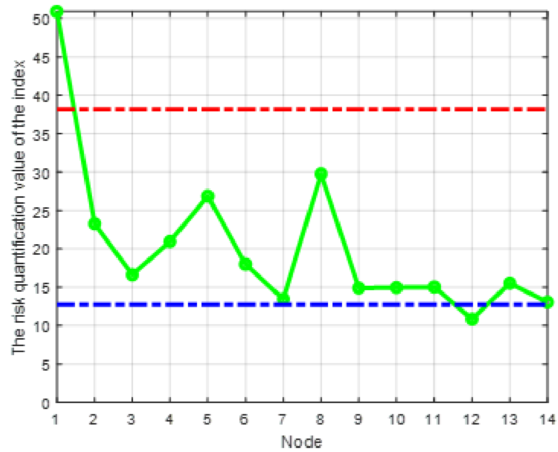
2) comparative analysis

The risk severity level k of the current operating state of the power communication network is obtained using Equation (25), and the risk value is calculated based on Equation (13),Equation (14), Equation (33), and Equation (34). This corresponds to observation case 1 in table 3. Additionally, the parameter value of the business index is modified to observe the comprehensive risk assessment results under different network conditions, as presented in table 3.

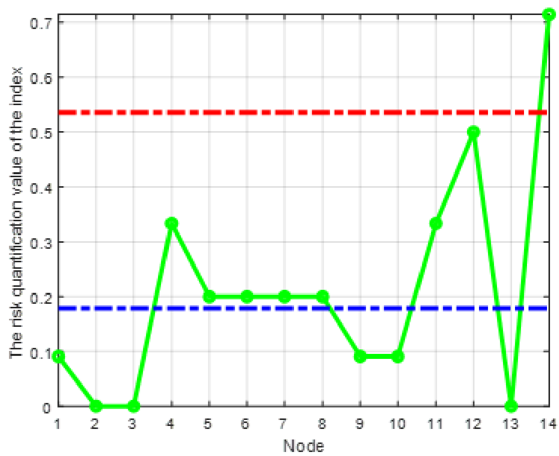
The difference between the actual network status of observation 1 and observations 2 and 3 is the variation in traffic volume. In observations 2 and 3, the amount of power traffic transmitted in the power communication network is gradually increased. The results indicate that, at the same probability



(a) Indicator C8



(b) Indicator C15



(c) Indicator C24

FIGURE 6. Risk index calculation results:(a) Indicator C8; (b) Indicator C15;(c) Indicator C24.

TABLE 3. Cloud clustering correlation degree of different states and evaluation results

Evaluation object	Cloud clustering correlation degree				Evaluation results		
	Serious	Abnormal	Attention	Good	The level of probability	The level of risk	The value of risk
Case 1	0.3548	0.2934	0.3219	0.5048	Grade 2	Attention	10.6494
Case 2	0.2400	1.0224	1.2334	0	Grade 2	Attention	20.8924
Case 3	0.2400	1.2678	0.9942	0	Grade 2	Abnormal	31.1355

TABLE 4. Comparison of evaluation results

Evaluation method	clustering correlation degree				Evaluation results	
	Serious	Abnormal	Attention	Good	The level of risk	The value of risk
Method of this article	0.3548	0.3314	0.3219	0.5048	Attention	10.6494
Gray clustering method	0.3638	0.3713	0.3477	0.5194	Attention	——
Matter-element extension	-1.2348	-0.6406	-0.6519	-0.6577	Abnormal	——
Fuzzy C-means clustering	0.1442	0.2816	0.306	0.2683	Attention	——

level, both the risk level and risk value increase when the business volume is doubled. When the business volume is increased by a factor of 1, the risk level remains unchanged, however, the risk quantification value can still explain the change in network state risk.

To further validate the evaluation results of the method proposed in this paper, we compared it with three other evaluation models: the traditional gray clustering evaluation model, fuzzy C-means clustering, and the matter-element extension model mentioned in literature [1]. The comparison results are presented in table 4. Additionally, table 5 displays the time and credibility required for the evaluation using these four methods under the same network conditions.

The results indicate that the traditional matter-element extension model is less accurate in determining the correlation degree. The correlation degree results for abnormal, attention, and good grades are very similar, making it prone to misjudgment. However, our method has an advantage over the gray clustering method as it includes both the comprehensive judgment of the risk level and the quantitative value of the risk. It introduces the risk probability level to further differentiate the risk level when the risk severity level is similar. Additionally, the network operation can be understood based on the risk value when the risk level is the same. The evaluation method's calculation discrimination degree is characterized by the difference between the final judgment result and its closest correlation degree. After performing calculations, the discrimination degree of this method is 0.1500, which is higher than the discrimination degrees of the gray clustering method (0.1481), the matter-element extension method (0.0113), and the fuzzy C-means clustering method (0.0244). It is evident that this method has the highest discrimination degree compared to the other methods. The result is similar to the gray clustering method, the only difference lies in the introduction of the cloud model and the consideration of the nature of the index. The clustering algorithm remains consistent, but the former method outperforms in terms of efficiency.

The traditional matter-element extension method calculates the correlation degree by measuring the extension distance between the index value and the index range. On the other hand, the fuzzy C-means clustering method calculates the correlation degree by considering the Euclidean distance from the index value to the clustering center. In contrast, the gray clustering method calculates the correlation degree using three different function types. However, the conventional gray clustering method fails to take into account the opposite effects of the benefit index and cost index on risk characteristics. This paper proposes an improved gray clustering method that addresses these limitations. Firstly, the cloud model is introduced to enhance the traditional whitening weight function. This allows for a more detailed division of intervals and the selection of the appropriate function type to calculate the correlation degree, thereby effectively capturing the fuzziness and randomness of the evaluation grade information. Secondly, the nature of the index is further distinguished, thereby avoiding the issue of index incompatibility. The experimental results confirm that this method exhibits the largest difference and provides the best evaluation of the risk level of power communication network. Table 5 demonstrates that the method proposed in this paper also excels in terms of time calculation and credibility.The dispersion degree of the simulation example results is evaluated by calculating the expected value of the evaluation results and conducting entropy analysis. The simulation example demonstrates that the evaluation results obtained using the method proposed in this paper are highly credible. In conclusion, the experimental results confirm that the proposed method has a better overall effect.

Finally, the weight coefficient of Equation (35) is analyzed and its value is changed. The results are shown in Figure 7.

It can be seen that when $\alpha<0.3$, the evaluation result is consistent with the level of probability, and when $\alpha>0.7$, the evaluation result is consistent with the severity level of risk.When $\alpha \in [0.3, 0.7]$,the risk assessment grade results are the same.In practical applications, the assessment of risk grading focus can be flexibly realized on demand according

TABLE 5. Evaluation method running time and credibility

Evaluation method	Method of this article	Gray clustering method	Matter-element extension	Fuzzy C-means clustering
Running time (1 time)/s	0.011276	0.044916	0.647153	0.003505
Running time (100 times)/s	1.06879	2.374	——	1.99272
Credibility δ	0	0.021	——	0.3571

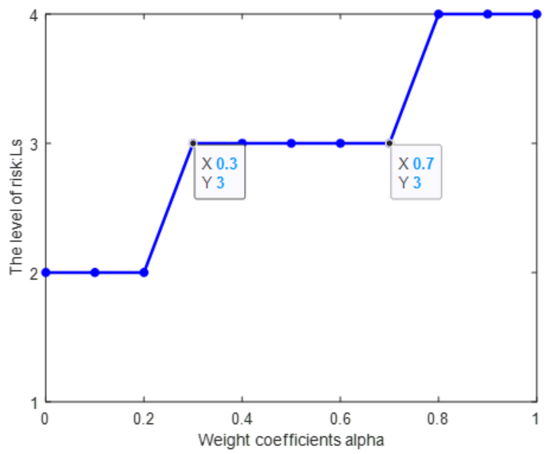


FIGURE 7. The evaluation results under different weight coefficient α.

to the actual operation of the network.

V. CONCLUSION

This paper presents a risk assessment method for power communication network that takes into account multiple risk factors. The study analyzes the risk factors associated with power communication network and establishes an evaluation index system based on the concept of 'static structure-dynamic operation'. A risk assessment model is developed by combining the matter-element extension model, gray theory, and cloud model theory. The proposed model utilizes the triangular modulus operator to calculate the probability of comprehensive risk occurrence, enabling both quantitative and accurate risk calculation and qualitative risk level evaluation for power communication network. The simulation results demonstrate that the business index and topology connectivity index are the primary risk factors. Furthermore, the method proposed in this paper outperforms three other risk evaluation methods in terms of credibility, efficiency, and discrimination, while also reducing the error in determining risk levels.

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