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Cloud model-based unconventional risk assessment method for flexible distribution system

Shaotao Guo [1], Peng Ye [1,*] , Jinhang Shan [1], Yi Liang [2], Zhentao Han [2], Qixiang Wang [2] and Na Zhang [2]

[1] Shenyang Institute of Engineering, Shenyang, 110136, China
[2] State Grid Liaoning Electric Power Co., Ltd. Economic and Technological Research Institute, Shenyang, 110013, China

Abstract

The integration of high-penetration distributed resources has led to increased complexity and uncertainty in the unconventional risks of distribution networks, posing higher demands on the risk assessment of distribution networks. This paper proposes an unconventional risk assessment method for flexible distribution system based on cloud model. Firstly, an unconventional risk assessment system for distribution networks is constructed by considering the probability of unconventional risk occurrence and the severe consequences, and an improved AHP-entropy weight method for index weighting is proposed. Then, the cloud model for risk assessment is used to quantitatively evaluate the risk level of the distribution system. The variable weight cloud model is employed to replace the traditional cloud model to provide risk indicator evaluation information. The inverse cloud generator is used to infer and correct the risk cloud model parameters, and the assessment is completed by comparing with the digital characteristics of the standard cloud model. Finally, the effectiveness of the proposed assessment method is verified through an example analysis of a certain region in China.

Keywords: Flexible distribution system, risk assessment, AHP-entropy weight method, cloud model, distributed resources.

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1. Introduction

As the deployment of distributed energy resources accelerates on a large scale, the penetration of renewable energy sources becomes significant, demanding a more adaptable system to manage the inherent variability and randomness. In response to this challenge, the integration of flexible distribution systems has been necessitated to maintain equilibrium in the face of widespread stochasticity. The flexible distribution system faces higher levels of uncertainty risks during operation, primarily manifesting in equipment failures and transmission line short circuits. Given the numerous uncertainties and potential risks inherent in the flexible distribution system, conducting an in-depth risk assessment is essential and urgent. As the flexible distribution system continues to evolve, traditional power system risk assessment methods are no longer fully applicable to the flexible distribution system. How to quantitatively assess the unconventional risks of the flexible distribution system under high-penetration distributed generation is becoming a research focus in the field of distribution network risk assessment.

Research on unconventional risk assessment for flexible distribution systems incorporating distributed resources has received considerable attention and interest from many scholars. [1] analyzed and established a theoretical system and risk assessment method suitable for risk assessment of distribution systems with high-penetration distributed sources. It characterized multi-source risk factors in the state generation stage and calculated multi-level risk indicators in the state analysis stage. The study also investigated a system vulnerability identification method that is organically integrated with risk assessment, providing a quantitative basis for risk pre-control decisions. [2] modeled the uncertain

*Corresponding author. Email: yepeng_126@sina.com

factors that cause protection misoperations, and based on this, established risk indicators for cascading faults in flexible interconnected distribution networks. A probability index based on Monte Carlo method and a calculation method based on optimal load shedding fault consequences were proposed. [3] analyzed the impact of distributed power penetration rate and SNOP (Soft Normally Open Points, SNOP) single-end capacity/line capacity on optimization strategies, and established a two-stage fault recovery model. The first stage used the minimization of load loss risk as the objective function, while the second stage introduced interval numbers to describe the uncertainty in distributed generation and load forecasting. Robust optimization was applied to optimize the operating state during fault recovery, and topology adjustments were made for cases that did not meet the constraints. [4] established a reliability evaluation model for flexible multistate switches, designed a load recovery method for the lost side, and extracted the factors that affect system reliability. To balance the speed and accuracy of reliability assessment, a reliability assessment method based on sequential sampling and decoupled fault analysis was proposed. Additionally, the impact of different access strategies for flexible multi state switches on system reliability was quantitatively analyzed. [5] effectively combined Monte Carlo simulation method and Latin hypercube sampling method to complete typical state sampling of distributed resources, considering the risk assessment of distribution networks with multiple distributed power sources. However, the risk assessment in the article did not consider multiple factors and cannot encompass all aspects of the distribution system. [6] proposed a joint planning model for multi-energy networks and energy hubs. Taking a multi-energy system with a high proportion of renewable energy installed capacity as an example, the impact of the proportion of renewable energy and load conditions on planning outcomes was analyzed. Utility theory has played a significant role in analyzing the severity of system failure consequences [7], [8]. [9] used regional control deviation as the antecedent of the cloud model generator, and simulated load disturbances under different conditions from both frequency and time domains. The cloud model controller is used to self-adjust the parameters of the PI controller, achieving load frequency control in the power system. [10] constructed a coupling model between the transportation network and the distribution network, utilizing the Monte Carlo sampling method to generate traffic flow distributions in multiple scenarios. [11] studied the stochastic fuzzy theory and stochastic fuzzy models in multi-energy systems, and proposed a stochastic fuzzy power flow model for multi-energy systems along with its computational method. The model considers the interconnection relationships between different systems. [12] considered the continuous increase of flexible resources within the new distribution system and the inability of traditional assessment methods to align with the development reality of the new distribution system, and constructs a novel framework for evaluating the flexibility of the new distribution system based on the cloud model. [13] considered the uncertainty of source and load, and established a two-stage distribution system fault model using the interval power flow method. On this basis, [14] used a dynamic rotation angle strategy to update the quantum gate and utilized a chaotic optimization method with Tent mapping to escape local optima. However, this literature only used reliability as an important indicator, which may not adequately reflect the influence of other factors on unconventional risks.

In summary, for distribution systems with high-penetration distributed energy resources, current research often considers risk assessment indicators from only a single aspect, and there is limited research on comprehensive risk assessment methods that consider multiple aspects. Furthermore, many studies focus on quantitative representation through the construction of operational stability indicators for power systems, without fully considering the interconnections between indicators and their comprehensive evaluation of the system's operational state. Aiming at the above problems, we first construct an unconventional risk assessment system for distribution networks that includes five key indicators: resilience, coordination, security, adequacy, and economy. An improved AHP-entropy (Analytic Hierarchy Process, AHP) weight method for index weighting is proposed. Subsequently, the risk assessment cloud model is employed to quantitatively evaluate the risk level of the distribution system. The variable weight cloud model is used to assign risk indicator evaluation information, and the inverse cloud generator is applied to deduce and modify the risk cloud model parameters. The assessment is completed by comparing the inferred parameters with the digital characteristics of the standard cloud model. Finally, the effectiveness of the proposed assessment method is verified through a case study analysis in a certain region of China.

2. Construction of the unconventional risk assessment system for flexible distribution systems

The risk assessment of the power distribution system aims to conduct a qualitative analysis of the uncertain risks that may be encountered during its operation. In this paper, the risk assessment of the distribution system is defined as the product of the probability of unconventional risks occurring in the power distribution network and the severity of the consequences they cause over a period of time, and its formula is given by

$$Risk\left(X_t\right)=\sum_i P_F\left(E_x\right)\bullet S_{ev}\left(E_x \mid X_t\right) \tag{1}$$

where X_t denotes the operational state of the distribution system at time t. E_x denotes the x-th unconventional risk. $P_F\left(E_x\right)$ denotes the probability of unconventional risk E_x occurring. $S_{ev}\left(E_x \mid X_t\right)$ denotes the severity of the harm caused by unconventional risk X_t under operational state E_x.

$Risk\left(X_t\right)$ denotes the assessment value of the unconventional risk for the distribution system under operational state X_t.

With the large-scale integration of high-penetration distributed energy resources today, the determination of $P_F\left(E_x\right)$ has become more complex. Addressing this issue, this paper employs Latin hypercube sampling to obtain typical scenarios of a power distribution system in a certain region, followed by using the equal dispersion sampling method to extract scenarios where components are in the failure interval from these typical scenarios. The corresponding severity of limit violations is calculated, and based on this severity, a determination is made as to whether a component has failed. This approach is used to comprehensively calculate the probability of unconventional risks occurring. For $S_{ev}\left(E_x | X_t\right)$, this paper considers five indicators that affect the unconventional risks of power distribution systems: resilience, coordination, security, adequacy, and economy, and constructs a risk assessment system, as shown in Figure 1. It should be noted that since the measurement of distribution system risk assessment depends on the current operational state of the system, the indicators for distribution system risk assessment require the establishment of a unified time scale as a prerequisite before calculation. The choice of time scale will determine the accuracy and complexity of the calculations.

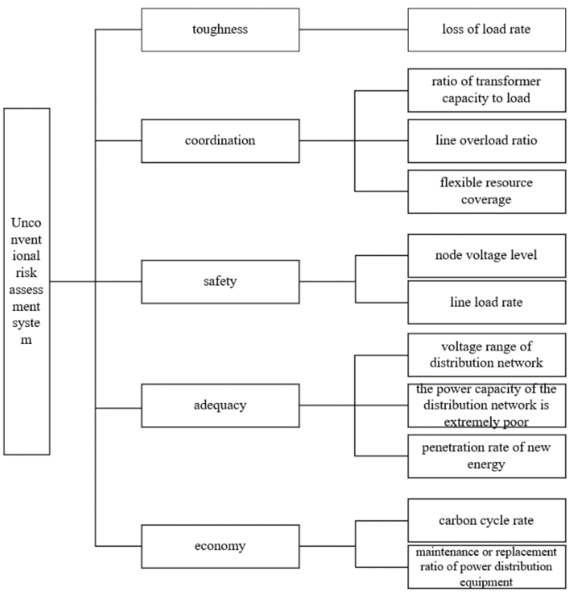

Figure 1. Unconventional risk assessment system for flexible distribution networks

The calculation methods for the five risk assessment indicators are as follows.

2.1 Calculation method for resilience

The resilience indicator of the flexible distribution network primarily considers the network's capacity to withstand risks, hence the definition of the third-level indicator as the load loss rate, and its formula is given by

$$v_{11} = \frac{P_{loss} - P_{re} - P_{mttr}}{P_w} \tag{2}$$

where P_{loss}, P_{re}, P_{mttr} and P_w denote the load loss during a risk event, the load amount managed by regional autonomy and intelligent self-healing control, the supplementary load amount provided by the system's flexible interconnection, and the total power supply load of the grid, respectively.

2.2 Calculation method for coordination

The coordination indicator of the flexible distribution network primarily considers the ability of the various devices within the distribution system to coordinate with each other. Therefore, the third-level indicators are defined as the variable capacitor load ratio, the line overload ratio, and the coverage rate of flexible resources, and its formula is given by

$$\begin{cases} v_{21} = \dfrac{S_{ei}(t)}{S_{\max}(t)} \\ v_{22} = \dfrac{m_{re}}{m_{ri}} \\ v_{23} = \dfrac{P_{RE}(t)}{P_{FR}(t)} \end{cases} \tag{3}$$

where $S_{ei}(t)$, $S_{\max}(t)$, m_{re}, m_{ri}, $P_{RE}(t)$ and $P_{FR}(t)$ denote the total capacity of grid transformers, the maximum installed capacity of the grid, the number of overloaded lines in the grid, the total number of all transmission lines in the grid, the total power of flexible resource loads, and the maximum power of the grid, respectively.

2.3 Calculation method for security

The security indicator of the flexible distribution network primarily considers the node voltage and power flow limit violation indicators within the distribution system. Therefore, the third-level indicators are defined as the extreme difference in node voltage of the distribution network, the extreme difference in line power, the extreme difference in equipment capacity, the penetration rate of new energy, and the load rate of new energy, and its formula is given by

$$\begin{cases} v_{31}(t) = \dfrac{1}{2}\left(\dfrac{\overline{U} - U(t)}{\overline{U}} + \dfrac{U(t) - \underline{U}}{\underline{U}}\right) \\ v_{32}(t) = \lambda_1 \sum \dfrac{P_{\max}^{ij} - P(t)}{P_{\max}^{ij}} + \lambda_2 \sum \dfrac{P(t) - P_{\min}^{ij}}{P_{\min}^{ij}} \\ v_{33}(t) = \dfrac{P_E(t)}{P_w} \end{cases} \tag{4}$$

where $\overline{U}$, $U(t)$, $\underline{U}$, $P_{\max}^{ij}$, $P(t)$, $P_{\min}^{ij}$, $P_E(t)$ and P_B denote the upper operational limit for node voltage, the node voltage during the distribution network's operation, the lower operational limit for node voltage, the maximum power transmission capacity of the grid's lines, the power transmission through lines during the distribution network's operation, the minimum power transmission capacity of the grid's lines, and the actual total operational load of the grid, respectively.

2.4 Calculation method for adequacy

The adequacy indicator of the flexible distribution network primarily considers the ability of the various devices within the distribution system to coordinate with each other. Therefore, the third-level indicators are defined as the extreme voltage difference in the distribution network, the extreme power difference in distribution network lines, the extreme capacity difference in distribution network equipment, the penetration rate of new energy, and the load rate of new energy, and its formula is given by

$$\begin{cases} v_{41}(t) = \dfrac{\overline{U}(t) - \underline{U}(t)}{U_N} \\ v_{42}(t) = \dfrac{P_{\max}^{ij}(t) - P_{\min}^{ij}(t)}{P_B} \\ v_{43}(t) = \dfrac{P_{D\max}(t) - P_{D\min}(t)}{P_D(t)} \\ v_{44}(t) = \dfrac{P_{RE}(t)}{P_E(t)} \\ v_{45}(t) = \dfrac{P_{RE}(t)}{P_w} \end{cases} \tag{5}$$

where $P_{D\max}(t)$, $P_{D\min}(t)$ denote the maximum and minimum power transmission capacities of the grid's lines, respectively.

2.5 Calculation method for economy

The economic indicator of the flexible distribution network primarily considers the operational costs and benefits of the distribution network. Therefore, the third-level indicators are defined as the carbon cycle rate and the rate of damage to distribution equipment, and its formula is given by

$$\begin{cases} v_{51}(t) = \sum_{t=1}^{T} c_{CO2}(t) P_{PV}(t) \\ v_{52}(t) = \dfrac{\sum_{t=1}^{T} S_{LOSS}(t)}{S_t} \end{cases} \tag{6}$$

where $c_{CO2}(t)$, $P_{PV}(t)$, $S_{LOSS}(t)$ and S_t denote the carbon emission cost per unit of power supply, the power output of photovoltaic sources, the number of damaged devices in the system, and the total number of devices in the system, respectively.

3. Risk assessment system weighting based on improved AHP-entropy weight method

AHP relies on expert opinions and experience to determine the relative importance of indicators, while entropy weighting starts from the data itself, quantifying the correlation and information content between indicators through the calculation of entropy. Both AHP and entropy weighting can consider the interrelationships between indicators, with entropy weighting being more objective and comprehensive in reflecting the importance of each indicator. However, the consistency test for entropy weighting is too complex, and the computational effort is excessive. In light of these issues, this paper proposes an improved AHP-entropy weighting method. This method not only maximizes the advantages of both methods but also enhances the accuracy and credibility of the evaluation results, simplifies the calculation process, and is suitable for the weighting of risks in high-penetration distributed generation distribution networks. The specific steps for weighting are as follows:

Step 1: After obtaining the original data of typical scenario operational states through sampling, AHP determines the weights of indicators at various levels through multiple rounds of collection of expert opinions.

Step 2: Establish a first level indicator judgment matrix ***A*** using the BWM proportional matrix method:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{7}$$

Where a_{ij} is given by

$$a_{ij} = \begin{cases} 1(\text{Indicator i is optimal}) \\ 0(\text{Neither indicator i nor indicator j is optimal}) \\ -1(\text{Indicator j is optimal}) \end{cases} \tag{8}$$

Step 3: Determine the optimal transmission matrix for matrix $\boldsymbol{A}$ as

$$B=\begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \tag{9}$$

Where B_{ij} is given by

$$B_{ij}=\frac{1}{n}\sum_{i=1}^{n}(a_{il}+a_{lj}) \tag{10}$$

Step 4: Determine the optimal consistency matrix for matrix $\boldsymbol{B}$ as

$$C=\begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{pmatrix} \tag{11}$$

where c_{ij} is given by

$$c_{ij}=\exp(b_{ij}) \tag{12}$$

Step 5: Determine weights v_1, v_2 and v_3 based on the optimal consistency matrix:

$$v_1=\frac{\left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}}},i=1,2,\cdots,n \tag{13}$$

$$Av_2=\lambda_{\max}v_2 \tag{14}$$

$$v_3=\frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n}a_{kj}},i=1,2,\cdots,n \tag{15}$$

where λ denotes the maximum eigenvector of the matrix.

Step 6: Based on the structure of the indicator system and the raw data, the entropy weight method is used to assign weights to the secondary indicators in the risk assessment system.

4. Unconventional risk assessment method for power distribution system based on cloud model

This paper uses the cloud model algorithm for qualitative evaluation of the quantitative indicators of unconventional risk levels in distribution systems.

4.1 Definition of Cloud Model

The cloud model is an uncertainty conversion model that combines probability with fuzzy mathematics. It represents the mapping relationship between qualitative concepts and quantitative values through the probability distribution of linguistic values. Let U denote the universe of discourse, which is the set of all possible values. For any element x in U, there exists a stable random variable Ex that represents the membership degree of x. If the elements in U are simply ordered, they can be considered as basic variables. If the elements in U are not simply ordered, they can be mapped to another ordered universe of discourse V through a mapping function f, such that each x has a unique corresponding v in V. The membership degree Ex then forms a membership cloud distribution on V, with each membership degree being referred to as a cloud droplet.

The cloud model describes the uncertain mapping relationship between qualitative concepts and quantitative values through membership cloud distribution. Its digital characteristics are composed of three parameters: expectation Ex, entropy Ex, and hyper entropy H_E. The relationship between the digital characteristics and the membership cloud is illustrated in Figure 2. Ex represents the expected distribution of cloud droplets on the quantified universe of discourse, reflecting the typical value of the quantified qualitative concept. En represents the uncertainty of the qualitative concept, which is determined by the randomness and ambiguity of the concept itself. He represents the overall uncertainty level of the cloud model.

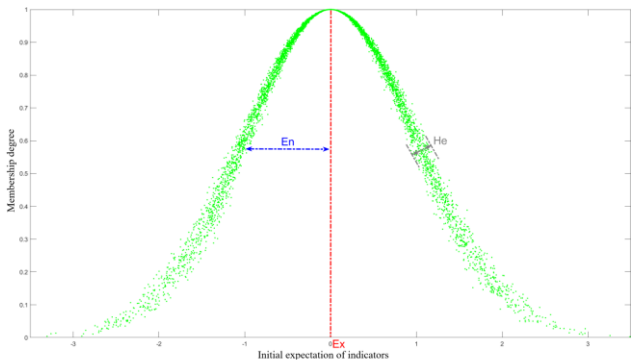

Figure 2. Cloud Model Digital Features and Membership Cloud Relationship Diagram

The cloud generator is a tool for achieving the mutual transformation between qualitative concepts and quantitative values. The generation algorithms for inverse clouds mainly fall into two categories: inverse cloud generation algorithms with certainty information and inverse cloud generation algorithms without certainty information. The inverse cloud generator employed in this paper is established on the basis of no certainty information, and its specific algorithm is as follows:

Step 1: The original data sample mean $\bar{X}=\frac{1}{n}\sum_{i=1}^{n}x_i$, first-order sample absolute central moment $\frac{1}{n}\sum_{i=1}^{n}\left|x_i-\bar{X}\right|$, and sample variance $S^2=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{X})^2$ obtained by calculating the sampling from cloud droplet x_i.

Step 2: Based on step 1, we can get

$$Ex=\bar{X} \tag{16}$$

$$En=\sqrt{\frac{\pi}{2}}\times\frac{1}{n}\sum_{i=1}^{n}\left|x_i-\bar{X}\right| \tag{17}$$

$$He=\sqrt{S^2-En^2} \tag{18}$$

4.2 Operation status of variable weight integrated power distribution system

To more accurately reflect the operational state of the distribution system, the variable weight theory is introduced into the cloud model [15], we can get

$$\omega_x=\frac{\omega_x^0\delta_x^{(\alpha-1)}}{\sum_{x=1}^{5}\left(\omega_x^0\delta_x^{(\alpha-1)}\right)} \tag{19}$$

where ω_x, ω_x^0 and δ_x are the variable weight, constant weight, and evaluation quantification values of the unconventional risk *x*, respectively. δ_x is obtained by weighted fusion of the quantification values of each indicator in the unconventional risk *x* and the corresponding indicator weights. And α is the equilibrium function, whose value determines the impact of each unconventional risk on the evaluation result. When $\alpha=1$, it is equivalent to the fixed weight mode. when $0.5\le\alpha<1$, it indicates that the requirement for balance is not high. when $\alpha<0.5$, it indicates that certain risks must be considered due to their severe consequences. Considering that any unconventional risk in the distribution system will affect system stability, according to the actual situation, α is set to -1 and w_x^0 is set to $1/5$. Using the variable weight fusion to obtain the risk assessment score, the comprehensive evaluation result is determined by the overall state of the distribution system based on the risk assessment levels.

4.3 Cloud evaluation method

This paper uses an inverse cloud generator to calculate the characteristic parameters of the cloud model according to the previously established unconventional risk evaluation indicators, thereby obtaining the risk assessment results based on the cloud model. The specific assessment process is as follows.

Step 1: Based on theoretical knowledge and expert decision-making, this study establishes unconventional risk rating standards and classifies risk status levels according to the four-level scale method. The standard risk cloud models for different risk levels are illustrated in Figure 3. The method of dividing the evaluation interval is shown in Table 1.

Table 1. Standard cloud parameters

Evaluation level	Interval division	Standard cloud parameters
High-risk	[0,30)	(15,12.7,0.6)
Medium-risk	[30,60)	(45,12.7,0.6)
Low-risk	[60,80)	(70,8.5,0.6)
Risk free	[80,100)	(90,5.85,0.6)

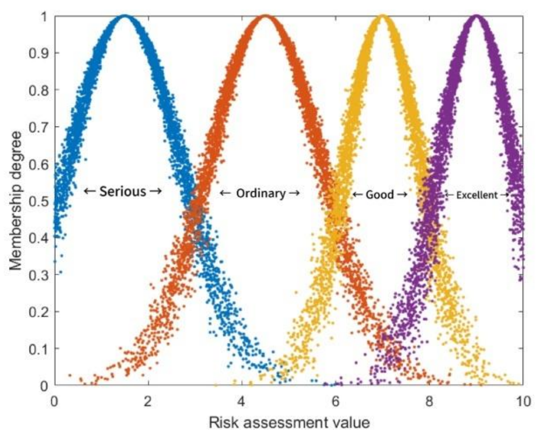

Figure 3. Risk assessment criteria cloud map

Step 2: Delving into each aspect of the power distribution system, this study collects actual operational data, filters and processes the data, and accurately calculates the digital characteristics of factors influencing risks. The calculation method is as follows:

$$\begin{cases} Ex_j=\bar{x}_j=\frac{1}{n}\sum_{i=1}^{n}x_{j,i} \\ S_j^2=\frac{1}{n-1}\sum_{i=1}^{n}(x_{j,i}-Ex_j)^2 \end{cases} \tag{20}$$

Step 3: Using a reverse cloud generator, the risk cloud model parameters are deduced based on actual data, and the calculation method is as follows:

$$\begin{cases} Ex_j = \bar{x}_j \\ En_j = \sqrt{\dfrac{\pi}{2}} \dfrac{1}{n} \sum_{i=1}^{n} | x_{j,i} - \bar{x}_j | \\ He_j = \sqrt{S_j^2 - En_j^2} \end{cases} \tag{21}$$

Step 4: Based on theoretical knowledge and experience, the cloud model parameters are modified, and the variable weighting method is used to weight the risk factors, resulting in a quantitative description of the current risk level in the variable weighting cloud model, and the calculation method is as follows:

$$\begin{cases} Ex_{j,k-1} = \sum_{j=1}^{n} Ex_{j,k} w_{j,k} \\ En_{j,k-1} = \sqrt{\sum_{j=1}^{n} En^2 w_{j,k}} \\ He_{j,k-1} = \sum_{j=1}^{n} He_{j,k} w_{j,k} \end{cases} \tag{22}$$

where w_j denotes the combined weight of the indicators.

Step 5: By comparing the characteristics of the risk cloud model obtained with the digital characteristics of the standard cloud model, the level of risk is determined, and the unconventional risks of the distribution system are completed.

The unconventional risk assessment process flowchart for the power distribution system in this paper is shown in Figure 4.

Figure 4. Flowchart of unconventional risk assessment for distribution systems

4.4 Unconventional risk probability estimation based on equal dispersion sampling method

The equal dispersion sampling method can improve the efficiency of unconventional risk assessment. It can reduce the number of sampling times while maintaining the same calculation accuracy. This method uses random numbers generated by sampling to simulate the fault state of the system, thereby improving computational efficiency. Due to its simplicity and feasibility, it is often applied in risk assessment systems. In the field of power grid, due to the low failure rate of power grid components, when using conventional sampling methods, the system status is usually normal or low fault state. This article uses the equal dispersion sampling method to generate more scenarios of system fault states, thereby accelerating convergence speed and improving simulation accuracy [16].

Step 1: According to the maximum outage rate of the system in the region, divide [0,1] into h sub intervals, and the length of the sub intervals satisfies

$$1/h \geq \max\{\lambda_1, \lambda_2, \ldots, \lambda_m\} \tag{23}$$

where $\lambda_1, \lambda_2, \ldots, \lambda_m$ denote the maximum outage rate of the system. Generating m random numbers represents m sampling iterations.

Step 2: Random numbers are drawn from the interval [0,1]. Based on the interval where the random number lies, it is determined whether the system is in a fault interval. If the system is in a fault interval, the severity of the node voltage and branch flow limit violations is calculated to determine whether the system is faulty. Otherwise, the system is in normal operation.

Step 3: Each sampling iteration corresponds to the fault state function of the flexible distribution system, as shown in Equation (24). The new state function is the average value of the fault state function of the flexible distribution system corresponding to a single sampling iteration.

$$F^*(X) = \sum_{k=1}^{h} F\left(X^k\right) / h \tag{24}$$

where $F\left(X^k\right)$ denotes a regular sampling function, and its corresponding partition interval is $\left[(k-1)/h, k/h\right]$.

Step 4: Using the new experimental function of the system to calculate the mathematical expectation is the probability of the system experiencing unconventional risk.

$$\hat{E}\left(F^*\right) = \sum_{i=1}^{m} F_i^*(X) / m \tag{25}$$

where F_i^* denotes the experimental function of the i-th sampling system.

5. Simulation analysis

A topology diagram was established based on the actual situation in a certain region of our country, as shown in Figure 5. This paper combines the measured data of the distribution network in this region for modeling and analysis. The model was developed using the YALMIP toolbox in MATLAB20, and the model was solved using the CPLEX solver.

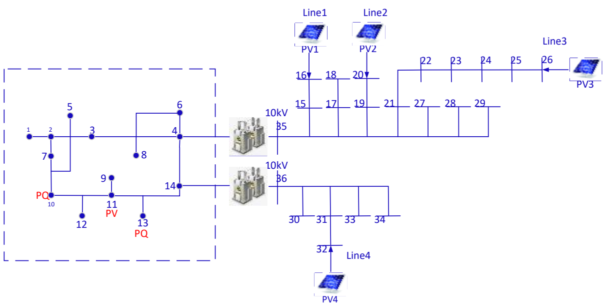

Figure 5. Topological structure of distribution network on a map in China

According to the construction situation of the distribution network in this region, the system's new energy penetration rate is 22.37%, with photovoltaic power stations located at nodes 16, 20, 26, and 32, and wind turbines located at node 16. The system also includes an energy storage station with a rated power of 1W and a capacity of 2Wh, located at node 16, with a charging and discharging efficiency of 92%. Additionally, there is a gas turbine unit with an installed capacity of 1W located at node 15, which operates at its minimum running power of 0…u. and maintains a normal startup status. Flexible loads can be dispatched with a capacity that accounts for 5% of the load capacity at the connected nodes, with 3% being movable loads located at node 22 and 2% being interruptible loads located at node 24. Moreover, SVC (Static Var Compensator) is connected at node 21 with a maxi-mum adjustable reactive power of 4var, and a reactive capacitor bank with a total of 4var is connected at node 18. The system allows voltage fluctuations within the range of 0…u. to 1…u.

5.1 Determination of weights for risk assessment system indicators

This paper uses the aforementioned improved AHP-entropy weighting method to determine the weights of the indicators in the risk assessment evaluation system. Through multiple rounds of collection of expert opinions, indicator transformation, and variable weight calculation, the weights of the indicators in the risk assessment evaluation system are obtained as shown in Table 2.

Table 2. Weights of risk assessment system indicators

Index	Subjective weight	Objective weight	Combined weight
v_{11}	0.0617	0.0372	0.0382
v_{21}	0.0463	0.0479	0.0252
v_{22}	0.0728	0.0452	0.0484
v_{23}	0.0676	0.0342	0.0135
v_{31}	0.081	0.0822	0.0751
v_{32}	0.0879	0.1413	0.1096
v_{33}	0.0804	0.0937	0.0877
v_{41}	0.0824	0.0535	0.0663
v_{42}	0.0368	0.0443	0.0404
v_{43}	0.0714	0.0500	0.0773
v_{44}	0.0726	0.1328	0.1543
v_{45}	0.0905	0.1442	0.1244
v_{51}	0.0894	0.0689	0.0638
v_{52}	0.0529	0.0729	0.0993

5.2 Analysis of system risk assessment results

According to the current status and future vision of the distribution system in this region, the study first generates typical scenarios using the aforementioned method. Then, it employs the equal dispersion sampling method to extract line fault scenarios and deter-mines whether they are faults based on their severity of limit violations. Subsequently, the line fault probability for this region is calculated. Figure 6 presents the risk of node voltage and branch flow limit violations for four randomly selected typical scenarios, and Figure 7 shows the probability of line faults obtained through sampling. The final calculation results in a line fault probability of 0.27% for this region.

Twelve representative line fault scenarios are randomly selected from a diverse sample set for risk assessment, ensuring that the selected scenarios encompass a wide range of potential risk scenarios. Subsequently, the risk assessment outcomes of each line fault scenario are analyzed, and the severity of the risk levels within the distribution system is compared. This analysis validates the feasibility of the proposed method in this paper, offering insights for the planning and operation of the distribution system in this region. The risk assessment results for scenarios 1 through 12 are depicted in Figure 8 to Figure 10.

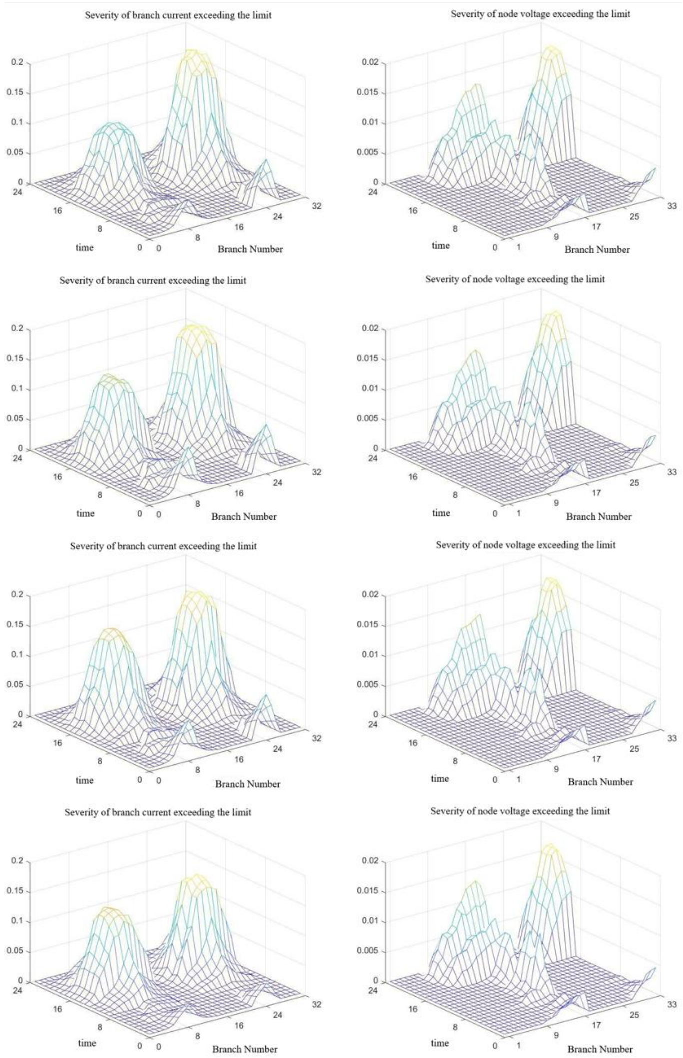

Figure 6. Risk maps of four typical scenarios exceeding limits

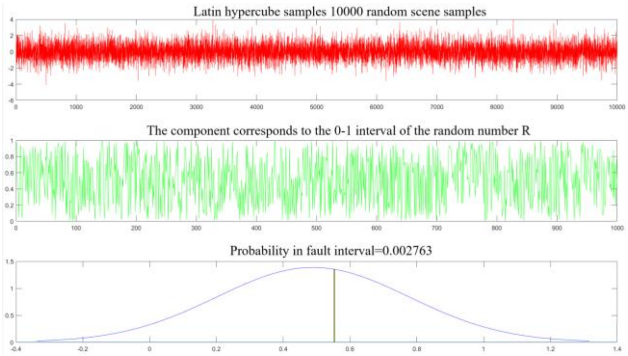

Figure 7. Sampling method for obtaining the probability of broken lines

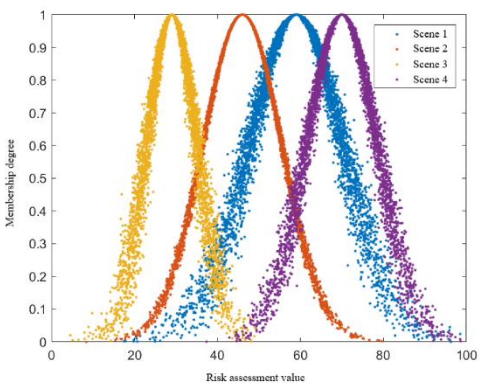

Figure 8. Scenarios 1-4 risk assessment results

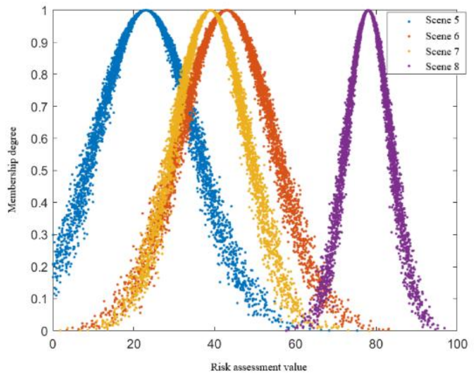

Figure 9. Scenarios 5-8 risk assessment results

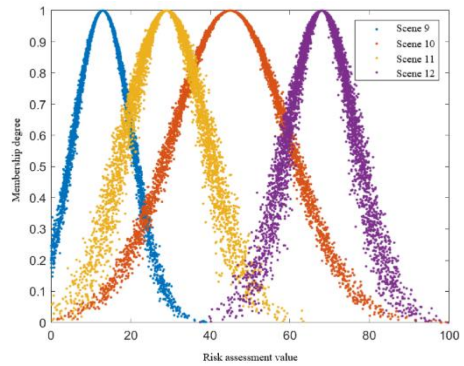

Figure 10. Scenarios 9-12 risk assessment results

Due to the concentration of the cloud model generation results, it is considered that the evaluation results are relatively stable. As depicted in the figures, the cloud droplets generated by the cloud models constructed from scenarios 3, 5, 9, and 11 primarily fall within the risk interval [0, 30]. The expected values for these four scenarios are 29, 23, 13, and 29, respectively, aligning most closely with the “High-risk” cloud in the standard cloud model. This indicates that these three scenarios are categorized as “High-risk.” The cloud droplets generated by the cloud models constructed from scenarios 1, 2, 6, 7, and 10 primarily fall within the risk interval [30, 60]. The expected values for these five scenarios are 59, 46, 39, 43, and 45, respectively, aligning most closely with the “Medium-risk” cloud in the standard cloud model, indicating that these five scenarios are categorized as “Medium-risk.” The cloud droplets generated by the cloud models constructed from scenarios 4, 8, and 12 primarily fall within the risk interval [60, 80]. The expected values for these three scenarios are 70, 78, and 68, respectively, aligning most closely with the “Low-risk” cloud in the standard cloud model, indicating that these three scenarios are categorized as “Low-risk”. To analyze the data more intuitively, the results are summarized and compared with the standard cloud parameters in Figure 11 and Figure 12.

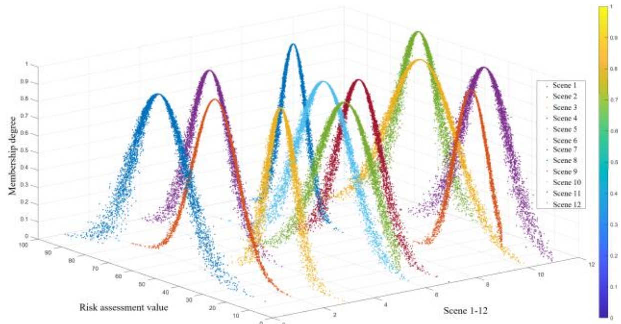

Figure 11. Summary of risk assessment results for scene 1-12

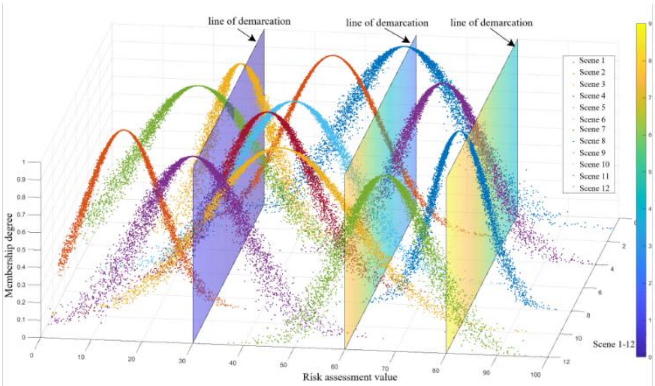

Figure 12. Comparison between evaluation results and standard cloud parameters

From the overall perspective of the power distribution network, the unconventional risk in this region is roughly at a moderate to high level. For high-risk scenarios, the integration of high penetration new energy may involve complex and variable factors, leading to increased system instability and potential problems. This high-risk characteristic may involve multiple levels, including challenges in technology, environment, and management. For medium risk scenarios, there is a certain degree of stability after timely regulation, but cautious management and monitoring are still needed. These scenarios may be challenging in some aspects, but they can relatively robustly address the uncertainty and potential issues of new energy access. For these scenarios, it is recommended to adopt more flexible management strategies in order to respond promptly to possible changes and challenges. The system in low-risk scenarios is relatively stable and the risk is controlled. This may reflect that effective management and control measures have been taken in these scenarios, and further optimization of management strategies can be considered to improve system performance. It is worth noting that no risk-free scenarios were found in this study, indicating that there are still potential risks in all scenarios after a disconnection occurs. Any control measures and means can only reduce the risk of the distribution system and cannot completely eliminate it.

The results indicate that the unconventional risk assessment method proposed in this paper can provide profound insights for risk assessment in the region, which aids in the formulation of comprehensive risk management strategies to ensure system stability and sustainability.

6. Conclusion

The integration of high-penetration distributed resources has increased the complexity and uncertainty of unconventional risks in power distribution networks, thereby raising the requirements for risk assessment in these networks. This paper proposes an unconventional risk assessment method for flexible distribution systems based on the cloud model. Initially, an unconventional risk assessment framework for power distribution networks is constructed by considering the probability of unconventional risk occurrence and the severity of its consequences, and an improved AHP-entropy weight method for index weighting is introduced. Subsequently, the risk assessment cloud model is employed to quantitatively evaluate the risk level of the distribution system. The variable weight cloud model is used in place of the traditional cloud model to assign evaluation information to risk indicators. The inverse cloud generator is applied to infer and correct the parameters of the risk cloud model, and the assessment is completed by comparing these parameters with the digital characteristics of the standard cloud model. Finally, a case study in a certain region of China is conducted, where 12 scenarios are randomly selected for risk assessment. The simulation results indicate that the unconventional risks in the region are at a moderate to high level, and the method proposed in this paper can provide accurate results for risk assessment in the region. We will further investigate multi-level probabilistic risk assessment, conducting comprehensive evaluations from the micro to the macro level to ensure that risk factors at all levels are fully considered.

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