Power System Risk Assessment Strategy Based on Weighted Comprehensive Allocation and Improved BP Neural Network

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Abstract

In the operation and maintenance process of the power system, factors such as power failures and supply-demand imbalances can have adverse effects on the normal power supply process. It is necessary to reduce or even solve this problem through corresponding power system risk warning. Based on this, the article proposes a self-assessment and early warning strategy for power system risks based on improved ant colony optimization algorithm (IACO) and BP neural network. Firstly, a combination of Analytic Hierarchy Process (AHP) and Entropy Weighting Method (EWM) is used to comprehensively assign weights to indicators that have a significant impact on the stability and safety of power system operation, avoiding the negative impact of subjective experience or objective factors on the weight allocation results. Secondly, multiple regression analysis is used to calculate the risk assessment results of the selected indicators and weights corresponding to the power system. According to the above weight allocation process, training and testing samples for the BP neural network were calculated and obtained. Then, IACO is used to global optimization the weights and thresholds of the BP neural network, and an improved BP neural network model for power system risk independent assessment is established. Finally, the designed risk assessment and warning strategy was tested. The results indicate that the proposed power system risk assessment and early warning method can accurately predict the actual working status of the power system based on weight values, providing data reference for technical personnel, and thereby improving power supply quality. Key words: Power system; Risk assessment; Comprehensive empowerment; Improved ant colony optimization algorithm; BP neural network.
model for power system risk independent assessment is established. Finally, the designed risk assessment and warning strategy was tested. The results indicate that the proposed power system risk assessment and early warning method can accurately predict the actual working status of the power system based on weight values, providing data reference for technical personnel, and thereby improving power supply quality.

Key words: Power system; Risk assessment; Comprehensive empowerment; Improved ant colony optimization algorithm; BP neural network

1 Introduction

The power system is an important infrastructure for social operation and economic development [1], and its stable and efficient operation is of great significance and value for ensuring national economic security and stable development [2-5]. The rapid development of the economy has led to the increasing scale of the power system and distribution network structure. In this development process, complex power supply system structures face enormous challenges in terms of safe operation and stable power supply. During the operation and maintenance of the power system, factors such as power failures, supply-demand imbalances, and changes in the working environment can have adverse effects on its normal operation, and even lead to power system paralysis [7-8]. Therefore, a comprehensive and accurate risk assessment and prediction of the power system can identify potential risk source and take corresponding control measures to ensure the operation safety and stability of the power system [9-10].

The risk assessment of the power system mainly considers the uncertainty factors within the system, and considers the risk as the possibility of the power system not meeting the established power supply indicators or suffering losses [11]. In order to accurately evaluate the potential risks of the power system, researchers have conducted large amounts of research work mainly based on reliability-based risk assessment methods [12]. Among them, reliability-based power system risk assessment is a relatively mature research field, including analytical methods [13], Monte Carlo simulation methods [14], etc. Reference [15] derived a sensitivity formula for the reliability indicators of power systems to vary with component reliability, effectively identifying weak links in system operation. Reference [16] simplified the power system and calculated its reliability through the fault impact matrix. Reference [17] uses multi-state Markov processes to describe the state of power plants and evaluates system risks using Lz transformations. The analytical method uses mathematical models to describe the faults of systems and components, with clear physical meanings and high accuracy of risk assessment results. However, the reliability parameters of this method are difficult to obtain, require a large amount of computation, and cannot be widely applied. Based on probability theory, Monte Carlo method uses different sampling methods to obtain the state of each component of the system, and then calculates the state response of the power system. Reference [18] combines equipment state sampling with traversal load path search to determine system state and calculate power system reliability. Reference [19] conducted a risk assessment of related faults in complex power systems caused by networks. Based on the summary of the above literature, it can be concluded that the applicability of the above achievements in identifying power system risk assessment is relatively small [20-21]. Further research and analysis are needed on how to expand the universal applicability of existing strategies for power system risk assessment when dealing with different power system models.

With the demand for intelligent development of distribution networks, research on risk assessment of power systems both domestically and internationally focuses on achieving stable power supply on the user side. The events, factors, or failure rates that result in the inability of the power system to maintain stable operation represent the operational risks of the power grid. The current mainstream method is to analyze and quantify the uncertain information of the power system operation process, and then provide feedback on the status of the power grid. Based on this, researchers established an indicator model for power system risk assessment based on the evaluation indicators of distribution network operation status. For example, reference [22] proposed an evaluation index system that covers grid connection characteristics, grid control characteristics, and operational characteristics. In terms of indicator selection and weight allocation, the AHP method has
strong subjectivity and arbitrariness, making it difficult to effectively display the changing characteristics of the importance of evaluation indicators [23]. The entropy weight method has outstanding advantages in mining the amount of information conveyed by the raw data of evaluation indicators, but it is difficult to effectively reflect the impact of expert experience on weight decision-making and evaluation models [24]. How to overcome the shortcomings of the above methods and obtain more accurate and reasonable weight allocation results is worth further research.

The theories and algorithms related to machine learning and artificial intelligence can perform online analysis and processing of data in changing systems and environments, determining the nonlinear relationships between data of different dimensions and categories, and have made rapid progress and widespread applications in recent years [25]. Artificial intelligence algorithms have significant advantages in processing large amounts of data and information, providing new ideas for risk assessment in power systems under complex information backgrounds. Reference [26] first applied artificial neural networks to risk assessment of power systems and achieved significant results. Literature [27] uses the principal component analysis method to select the indicators that affect the reliability of the power system, and uses relevance vector machine to evaluate the reliability of the power system. BP neural networks can be trained through backpropagation algorithms and have wide applications in solving nonlinear correspondence, becoming a research hotspot in the field of independent risk assessment of power systems. Reference [28] proposed a risk assessment model for deep excavation construction based on improved AHP and BP neural network, and used BP neural network to predict the risk level. Reference [29] uses wavelet BP neural network to evaluate and warn the risk level of the supply chain. As research deepens, researchers gradually begin to optimize the weights and thresholds of traditional BP neural networks to improve their convergence ability and prediction accuracy. For example, reference [30] utilized an improved ant lion algorithm to optimize the weights and thresholds of the BP neural network, improving its prediction accuracy.

The remaining part of the article is expanded as follows: Section 2 determines the evaluation indicators for power system risks; The third section uses the comprehensive weight allocation method to assign weights to the indicators; Section 4 establishes a power system risk assessment and prediction model based on IACO and BP neural network; Finally, Section 5 summarizes the article and proposes future development directions.

2 Risk assessment indicators for power system

In order to quantitatively evaluate and warn of power system risks, it is necessary to select key indicators that have a significant impact on power system risks for analysis. When selecting corresponding indicators, full consideration should be given to multiple factors in the actual operation of the power system, in order to improve the accuracy, objectivity, and comprehensiveness of the risk assessment model.

2.1 Principles for selecting indicators

With the continuous expansion of the scale of the power system and the complexity of its internal structure, it is difficult to directly obtain or the process of obtaining data related to some power system risks is extremely cumbersome. Therefore, when establishing a risk assessment and early warning model for the power system, in order to ensure scientificity, effectiveness, and standardization, the process of selecting indicators should follow the following principles:

(1) Principle of logic

The principle of logicality refers to the inherent logical relationship between the selected indicators and risk types when selecting key indicators to evaluate the risks in the operation process of the power system. On the other hand, the selected indicator set should have the ability to fully reflect power system risk related information and inducing factors from different dimensions.

(2) Principle of directionality
When constructing an evaluation model for evaluating power system risks, it is necessary to take multi-dimensional factors such as specific work scenarios, load characteristics, and power supply environment as the basis, emphasizing the pertinence of the selected indicators for the evaluation object. In fact, a comprehensive evaluation model designed for a specific object can only be used for performance evaluation and prediction of that object. When the object changes, targeted adjustments should be made.

(3) Principle of convenient operation

Convenient operability is an important feature of constructing power system risk assessment models, which is related to the accuracy and credibility of data samples. When selecting indicators, full consideration should be given to the difficulty and cost of obtaining indicator data. The real data of some indicators is difficult to obtain in actual working environments, which can have an impact on the risk assessment model of the power system.

(4) Principle of efficiency

In the current production environment, complex substation equipment systems require high response speed and computational power for corresponding risk assessment models. When constructing the corresponding evaluation system, the principle of convenience should be emphasized. Utilize existing data processing algorithms to reduce computational burden and accelerate model response speed.

2.2 Evaluation indicators

Consider the main impacts of distribution network power supply reliability, power supply capacity, power quality, and network structure. The following indicators are selected to construct a risk assessment model.

<table>
<thead>
<tr>
<th>Primary indicators</th>
<th>Indicator number</th>
<th>Secondary index</th>
<th>Indicator number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power supply reliability</td>
<td>A</td>
<td>Equipment failure rate</td>
<td>A1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average interruption hours of customer</td>
<td>A2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average number of power outage users</td>
<td>A3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Old equipment rate</td>
<td>A4</td>
</tr>
<tr>
<td>Power supply capacity</td>
<td>B</td>
<td>Power capacity rate</td>
<td>B1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Line overload ratio</td>
<td>B2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Supply and storage ratio</td>
<td>B3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Consumption ratio</td>
<td>B4</td>
</tr>
<tr>
<td>Electrical energy quality</td>
<td>C</td>
<td>Three-phase unbalance</td>
<td>C1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Nonlinear load rate</td>
<td>C2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Impact load rate</td>
<td>C3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average qualified rate of Grid connected node voltage</td>
<td>C4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average qualified rate of grid connected node current</td>
<td>C5</td>
</tr>
<tr>
<td>Grid structure</td>
<td>D</td>
<td>Grid interconnection rate</td>
<td>D1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average power supply radius</td>
<td>D2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Insulation rate</td>
<td>D3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>line loss rate</td>
<td>D4</td>
</tr>
</tbody>
</table>

3 Index weight allocation and comprehensive evaluation

After determining the power system risk assessment indicators shown in Tab.1, it is necessary to allocate weights based on the impact characteristics of each indicator on power system risk in the actual system. AHP is a decision analysis method that determines the relative importance of multiple indicators or factors.
in the overall hierarchy by comparing and analyzing them. AHP has the advantages of simple structure and convenient operation, making it widely used. However, AHP has subjectivity in determining the hierarchical structure and determining the importance of indicators, and is not suitable for designing complex decision-making problems with many factors. Therefore, the article utilizes AHP and EWM to jointly allocate weights to the indicators of the power system risk assessment model, considering both subjective and objective factors to improve the accuracy and credibility of the results.

3.1 AHP

The commonly used approach to determine the weight of evaluation indicators using the AHP method is to decompose the research object into multiple independent sub factors. Based on the internal coupling characteristics between different sub factors, a multi-level evaluation model is established by combining them according to the hierarchical division. Establish the following discriminant matrix using the three-scale method

where is used to represent the importance of relative to. Determine importance indicators by comparing multiple factors in pairs. Whentakes a value of 1, it indicates that is more important than , and vice versa, it indicates that is more important than .

After determining the discriminant matrix, determine the optimal transfer matrix \( \mathbf{L} \) for the above discriminant matrix \( \mathbf{A} \):

The relationship between the corresponding elements in the transmission matrix and the corresponding elements in the discrimination matrix \( \mathbf{A} \) satisfies the following equation:

In addition, the optimal consistency matrix \( \mathbf{X} \) of the optimal transfer matrix \( \mathbf{L} \) can be expressed as:

where can be determined by .

Calculate the geometric mean value of elements in the discrimination matrix \( \mathbf{A} \) by the following formula:

Normalizing the obtained from Eq. can determine the weight of each indicator in the AHP method, which can be expressed as:

3.2 Entropy weight method

Unlike the principle of AHP using subjective experience to weight indicators, EWM is a weighting method that starts from objective factors. In the practical application process, it is mainly based on the information entropy to calculate the index entropy weight of different influence degrees, and then the entropy weight is used to process each index to get the result. Assuming that the evaluation matrix of the power system risk assessment model is , and when calculating the indicator weight using the EWM method, the weight ratio of under indicator can be expressed as:

The entropy value of indicator can be expressed as:

Therefore, the entropy weight of the indicator is defined as:

Considering the impact of different factors on the collected data of each indicator, such as data loss and pollution, the weights of the evaluation indicators are normalized:

whereandrepresent the normalized weight value and initial weight value of evaluation indicator, respectively;and represent the adjusted number of indicators and evaluation indicator, respectively.
3.3 Comprehensive weight allocation

For the power system risk assessment model, some risk factors largely depend on the operational experience of technical personnel in the past power system repair and maintenance processes. When establishing a comprehensive assessment model for power system risk, emphasis should be placed on considering the weight proportion determined based on human experience, and increasing the proportion of the weight obtained by the AHP method in the total weight. Therefore, the final weight of each evaluation indicator is:

where represents the weight value of the indicator under the AHP method; represents the weight value of the above indicators under the entropy weight method.

Summarize the above analysis and use AHP and EWM to comprehensively assign weights to various indicators of the power system risk assessment model. The weight allocation results of each primary indicator and corresponding secondary indicators are shown in Tab.2.

Tab.2 Indicator selection results of power system risk assessment model

<table>
<thead>
<tr>
<th>Primary indicators</th>
<th>Weight</th>
<th>Secondary indicators</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.3247</td>
<td>A1</td>
<td>0.3325</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>0.1742</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A3</td>
<td>0.2069</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A4</td>
<td>0.2864</td>
</tr>
<tr>
<td>B</td>
<td>0.3056</td>
<td>B1</td>
<td>0.1463</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B2</td>
<td>0.2844</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B3</td>
<td>0.1975</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B4</td>
<td>0.3718</td>
</tr>
<tr>
<td>C</td>
<td>0.1943</td>
<td>C1</td>
<td>0.2312</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C2</td>
<td>0.1430</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C3</td>
<td>0.1713</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C4</td>
<td>0.2931</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C5</td>
<td>0.1614</td>
</tr>
<tr>
<td>D</td>
<td>0.1754</td>
<td>D1</td>
<td>0.2454</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D2</td>
<td>0.2968</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D3</td>
<td>0.1524</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D4</td>
<td>0.3054</td>
</tr>
</tbody>
</table>

3.4 Risk assessment of power system

After determining the comprehensive weights of various indicators in the power system risk assessment model based on the above analysis, the multiple regression analysis algorithm is used to calculate the corresponding scoring values for different data. Use the following regression equation to describe the relationship between evaluation indicators and scores:

In the formula, represents the scoring value corresponding to the evaluation indicator data; represents the regression coefficient; represents the independent variable; represents the random error distribution term, satisfying .

When using multiple regression equations to evaluate the risk of the distribution network power system, it is necessary to determine the corresponding samples of the evaluation indicators through independent tests to estimate the regression coefficient mentioned above.
4 Autonomous Risk Assessment and Early Warning Strategy for Power System

After weighting the selected indicators according to the weight comprehensive allocation strategy of power system risk indicators established in Section 3, the corresponding indicator values and comprehensive risk assessment results for each power system can be determined through multiple regression equations. By using the corresponding relationships between multiple sets of power system indicator data and comprehensive evaluation results as samples to train BP neural networks, the adaptive advantages of neural networks can be utilized to analyze the complex nonlinear relationship between data and risk, achieving autonomous assessment and early warning of power system risks. The idea of the power system risk independent assessment and early warning strategy designed in the article is shown in Fig.1.

Fig.1 Concept of risk independent assessment and early warning strategies for power systems

4.1 Improved Ant Colony Optimization Algorithm

When ant colony algorithm optimizes and solves complex nonlinear problems, it draws inspiration from the natural thinking of ants foraging. When ants pass a certain road, they will release pheromone, which will guide the follow-up ants to move towards the direction of higher pheromone concentration. On this basis, the large-scale movement of ant colony can form a positive feedback mechanism about pheromone. The path with less pheromone accumulation will eventually disappear with the decrease of ants and the dissipation of pheromone. Based on the path search and optimization of the ant colony, the optimal path can be determined.

In the process of finding the optimal solution, the ants determine the subsequent path by sensing the pheromone concentration. Therefore, the pheromone in the ant colony algorithm plays a vital role in the overall performance of the algorithm. The traditional ant colony algorithm only has the global pheromone update method, that is, the pheromone on the path is only updated in the iterative process. This update method not only affects the search speed of the algorithm, but may also lead to the algorithm falling into
a local optimal solution. In order to avoid the above shortcomings, the pheromone update method with adaptive volatility coefficient and the best worst reward and punishment mechanism are used to iterate the pheromone update to improve the pheromone update strategy of the ant colony algorithm.

According to the above analysis, the updating formula of pheromone with adaptive volatility coefficient proposed in the article can be expressed as:

where represents the pheromone between node and node; represents the adaptive volatilization factor of pheromone.

The adaptive volatilization factor is designed as:

where represents the initial value set during the initialization phase; represents the number of cycles; is the maximum number of cycles.

The global pheromone update formula including reward mechanism can be expressed as:

In the above global pheromone update formula, there are:

where represents the pheromone left by ant between node and node in the process of iteration.

According to the above local pheromone update and the best worst reward and punishment mechanism iteration pheromone formula, the ant colony optimization algorithm can be improved to improve the optimization performance of the algorithm.

4.2 Risk assessment strategy based on BP neural network

BP neural network is a feedforward network that transmits signals forward and errors backward. It is commonly used for predicting uncertain systems and has the advantages of strong learning ability and high prediction accuracy. The structure of the BP neural network is shown in Fig.2.

![Fig.2 Structure of BP neural network](image-url)
In order to improve the fitting ability of BP neural network, sigmoid function is used as the activation function. The loss function selects the cross-entropy function to measure the difference between the output value and the true value of the BP neural network:

where and represent the target and actual values of the BP neural network, respectively; represents the number of output nodes.

Although the traditional BP neural network model has good performance when applied to nonlinear system prediction, there are still some problems such as slow convergence speed and easy to fall into local optimization. The development of swarm intelligence algorithm provides a new idea for improving the prediction performance of BP neural network. Based on this, when determining the weight and threshold parameters of the BP neural network, the article uses an improved ant colony optimization algorithm to make optimization decisions. In addition, the mutation factor is introduced in the above optimization process to obtain the optimal weight and threshold combination of the BP neural network in the current scenario.

The specific steps to determine the optimal weight and threshold of the BP neural network using ant colony optimization algorithm are as follows:

1. Initialize ant colony parameters. Set the number of ants in optimization as , the initial pheromone of the elements contained in the set as , and the maximum number of iterations in the optimization process as .

2. In each optimization step, start all ants for optimization. For ant , the probability of the selected ant element is determined according to the pheromone concentration value of each element. Adopt the roulette theory random selection probability as described in the following equation:

where represents the pheromone concentration of the ant element; represents the visibility of the ant element; represents the pheromone concentration of the ant element ; represents the visibility of the ant element.

3. During the optimization process, all ants select elements and are considered to have found food. Establish a BP neural network model based on the element selection characteristics of ants, and input the optimized training data. Calculate the function value according to Eq. to represent the path traveled by each ant.

4. Select ants with the shortest path distance to return to the starting point along the original route, and update its pheromone at the same time. The time experienced by ants is . The ant’s pheromone concentration is updated according to the designed pheromone updating method including adaptive volatility coefficient and the optimal worst reward and punishment mechanism iterative pheromone formula.

5. Repeat steps (2) - (4) until all ants in the optimization process converge to the same path or reach the maximum number of iterations.

4.3 Results and analysis

The risk assessment of the power system should have real-time and accurate characteristics. Based on this, this article uses BP neural network to achieve independent risk assessment of specific power systems under indicator data, improving assessment accuracy while reducing the time consumption of the calculation process. When simulating and testing the proposed research idea in MATLAB software, taking the actual operation data of a certain city’s power system as an example, after removing incomplete and defective data, a total of 700 sets of data were finally obtained as sample data for BP neural network training and testing. The type of data matrix is the corresponding values of each indicator and the comprehensive evaluation results, with a dimension of 17*701. During simulation, set the number of input layer nodes to 17 and the number of output layer nodes to 1. In addition, assuming that the comprehensive score of power system risk is determined using multiple regression analysis algorithm (with a score distribution interval of [0,100]), the score is divided into four intervals as shown in Tab.3 to describe the actual working conditions of the power system.
Tab.3 Dividing intervals of power system risk assessment results

<table>
<thead>
<tr>
<th>Risk level</th>
<th>Scoring range</th>
<th>Number</th>
<th>Operation suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0-20</td>
<td>1</td>
<td>No action required, continue running</td>
</tr>
<tr>
<td>Medium</td>
<td>20-30</td>
<td>2</td>
<td>Maintain according to regulations</td>
</tr>
<tr>
<td>Attention</td>
<td>30-40</td>
<td>3</td>
<td>Real-time monitor</td>
</tr>
<tr>
<td>Abnormal</td>
<td>40-100</td>
<td>4</td>
<td>Immediate repair</td>
</tr>
</tbody>
</table>

Select 650 sets of data from the identified data samples as training samples for the BP neural network. To avoid the subjectivity of manually selecting data during the training of neural networks, the process of selecting training samples is completed using random functions. The remaining 50 sets of data are used for risk assessment accuracy testing of the BP neural network model.

In fact, the more nodes in the hidden layer, the better. A relatively large number of hidden layer neurons will seriously increase the computational burden and reduce the overall prediction performance. The number of hidden layer nodes is determined according to the following empirical formula:

where and represent the number of nodes in the input layer and output layer, respectively; represents a random integer; represents the number of nodes in the hidden layer, and after calculation, its range is determined to be [6,14].

When determining the number of hidden layer nodes, the equality coefficient described in the following equation can be used as the evaluation indicator. The closer this value is to 1, the better the predictive performance of the BP neural network under the number of nodes in this hidden layer:

where represents the total number of predicted samples; and represent actual and predicted values, respectively.

According to Eq., calculate the data accuracy of the proposed key secondary equipment fault prediction algorithm during training when the number of hidden layer nodes changes, as shown in Fig.3. According to the variation curve of prediction accuracy corresponding to different hidden layer nodes shown in Fig.3, when the number of hidden layer nodes is 10, the BP neural network model has the highest prediction accuracy. Therefore, the number of hidden layer neurons in the BP neural network selected for power system risk assessment is 10.

where represents the prediction accuracy of the BP neural network; and represent the number of correctly predicted samples and the total number of samples, respectively.
After the training of the power system risk assessment model based on BP neural network is completed, the accuracy of the trained BP neural network is tested using the remaining 50 sets of data. The test results are shown in Fig.4. According to Fig.4 (a), the research idea proposed in this paper to use IACO algorithm to global optimization the weights and thresholds of BP neural network for power system risk assessment is effective. Among the 50 sets of sample data used to test the prediction accuracy of the BP neural network, the error between the predicted results and the actual results corresponding to the sample data is relatively small. In addition, according to Fig.4 (b), the predicted risk levels corresponding to Tab.3 obtained from the proposed power system risk assessment and warning strategy are almost identical to the actual risk interval corresponding to the data. Among all 50 sets of data, only one set of predicted results did not match the actual results. From the perspective of risk distribution level prediction, the proposed BP neural network based on IACO optimization has a prediction accuracy of 98%. Therefore, this model can effectively and accurately predict the actual working state of the power system, and has good application prospects.
Afterwards, in order to verify the impact of the proposed method of using IACO to optimize the weights and thresholds of the BP neural network on the prediction accuracy of the BP neural network, the article randomly selected 5 sets of data from the above 700 sets for testing, and the results are shown in Fig.5. According to Fig.5, IACO can improve the prediction accuracy of BP neural networks by adjusting their weights and thresholds, resulting in smaller prediction errors than traditional BP neural networks. When not optimized by IACO, the prediction accuracy of traditional BP neural networks is relatively low, with one of the five sets of test data experiencing incorrect predictions (Fig.5 (b)).

5 Conclusion

In order to reduce the adverse impact of potential risks in the power system on normal power supply, the article proposes a power system risk assessment and warning strategy based on IACO and BP neural network. The main conclusions of the article are as follows:

(1) The combination method of AHP and EWM is used to comprehensively assign weights to indicators that have a significant impact on the stability and safety of power system operation, achieving a balanced consideration of subjective experience and objective factors, and improving the credibility of evaluation
results. Afterwards, multiple regression analysis is used to calculate the risk assessment results of the selected indicators and weights corresponding to the power system.

(2) According to the above weight allocation process, training and testing samples for the BP neural network were calculated and obtained. At the same time, IACO is used to global optimization the weights and thresholds of BP neural network, which improves the convergence ability and prediction accuracy of BP neural network.

(3) The test results validate the effectiveness and accuracy of the proposed risk assessment and warning strategy for power systems using IACO and BP neural networks, which can significantly improve power supply quality and have significant application prospects.

In future research, we will continue to study high-performance prediction algorithms to further obtain a power system risk warning mechanism with simple calculation and high accuracy.

Reference


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Abstract: In the operation and maintenance process of the power system, factors such as power failures and supply-demand imbalances can have adverse effects on the normal power supply process. It is necessary to reduce or even solve this problem through corresponding power system risk warning. Based on this, the article proposes a self-assessment and early warning strategy for power system risks based on improved ant colony optimization algorithm (IACO) and BP neural network. Firstly, a combination of Analytic Hierarchy Process (AHP) and Entropy Weighting Method (EWM) is used to comprehensively assign weights to indicators that have a significant impact on the stability and safety of power system operation, avoiding the negative impact of subjective experience or objective factors on the weight allocation results. Secondly, multiple regression analysis is used to calculate the risk assessment results of the selected indicators and weights corresponding to the power system. According to the above weight allocation process, training and testing samples for the BP neural network were calculated and obtained. Then, IACO is used to global optimization the weights and thresholds of the BP neural network, and an improved BP neural network model for power system risk independent assessment is established. Finally, the designed risk assessment and warning strategy was tested. The results indicate that the proposed power system risk assessment and early warning method can accurately predict the actual working status of the power system based on weight values, providing data reference for technical personnel, and thereby improving power supply quality.

Key words: Power system; Risk assessment; Comprehensive empowerment; Improved ant colony optimization algorithm; BP neural network

1 Introduction

The power system is an important infrastructure for social operation and economic development [1], and its stable and efficient operation is of great significance and value for ensuring national economic security and stable development [2-5]. The rapid development of the economy has led to the increasing scale of the power system and distribution network structure. In this development process, complex power supply system structures face enormous challenges in terms of safe operation and stable power supply. During the operation and maintenance of the power system, factors such as power failures, supply-demand imbalances, and changes in the working environment can have adverse effects on its normal operation, and even lead to power system paralysis [7-8]. Therefore, a comprehensive and accurate risk assessment and prediction of the power system can identify potential risk source and take corresponding control measures to ensure the operation safety and stability of the power system [9-10].

The risk assessment of the power system mainly considers the uncertainty factors within the system, and considers the risk as the possibility of the power system not meeting the established power supply indicators or suffering losses [11]. In order to accurately evaluate the potential risks of the power system, researchers have conducted a large amount of research work mainly based on reliability-based risk assessment methods [12]. Among them, reliability-based power system risk assessment is a relatively mature research field, including analytical methods [13], Monte Carlo
simulation methods [14], etc. Reference [15] derived a sensitivity formula for the reliability indicators of power systems to vary with component reliability, effectively identifying weak links in system operation. Reference [16] simplified the power system and calculated its reliability through the fault impact matrix. Reference [17] uses multi-state Markov processes to describe the state of power plants and evaluates system risks using IZ transformations. The analytical method uses mathematical models to describe the faults of systems and components, with clear physical meanings and high accuracy of risk assessment results. However, the reliability parameters of this method are difficult to obtain, require a large amount of computation, and cannot be widely applied. Based on probability theory, Monte Carlo method uses different sampling methods to obtain the state of each component of the system, and then calculates the state response of the power system. Reference [18] combines equipment state sampling with traversal load path search to determine system state and calculate power system reliability. Reference [19] conducted a risk assessment of related faults in complex power systems caused by networks. Based on the summary of the above literature, it can be concluded that the applicability of the above achievements in identifying power system risk assessment is relatively small [20-21]. Further research and analysis are needed on how to expand the universal applicability of existing strategies for power system risk assessment when dealing with different power system models.

With the demand for intelligent development of distribution networks, research on risk assessment of power systems both domestically and internationally focuses on achieving stable power supply on the user side. The events, factors, or failure rates that result in the inability of the power system to maintain stable operation represent the operational risks of the power grid. The current mainstream method is to analyze and quantify the uncertain information of the power system operation process, and then provide feedback on the status of the power grid. Based on this, researchers established an indicator model for power system risk assessment based on the evaluation indicators of distribution network operation status. For example, reference [22] proposed an evaluation index system that covers grid connection characteristics, grid control characteristics, and operational characteristics. In terms of indicator selection and weight allocation, the AHP method has strong subjectivity and arbitrariness, making it difficult to effectively display the changing characteristics of the importance of evaluation indicators [23]. The entropy weight method has outstanding advantages in mining the amount of information conveyed by the raw data of evaluation indicators, but it is difficult to effectively reflect the impact of expert experience on weight decision-making and evaluation models [24]. How to overcome the shortcomings of the above methods and obtain more accurate and reasonable weight allocation results is worth further research.

The theories and algorithms related to machine learning and artificial intelligence can perform online analysis and processing of data in changing systems and environments, determining the nonlinear relationships between data of different dimensions and categories, and have made rapid progress and widespread applications in recent years [25]. Artificial intelligence algorithms have significant advantages in processing large amounts of data and information, providing new ideas for risk assessment in power systems under complex information backgrounds. Reference [26] first applied artificial neural networks to risk assessment of power systems and achieved significant results. Literature [27] uses the principal component analysis method to select the indicators that affect the reliability of the power system, and uses relevance vector machine to evaluate the reliability of the power system. BP neural networks can be trained through backpropagation algorithms and have wide applications in solving nonlinear correspondence, becoming a research hotspot in the field of independent risk assessment of power systems. Reference [28] proposed a risk assessment model for deep excavation construction based on
improved AHP and BP neural network, and used BP neural network to predict the risk level. Reference [29] uses wavelet BP neural network to evaluate and warn the risk level of the supply chain. As research deepens, researchers gradually begin to optimize the weights and thresholds of traditional BP neural networks to improve their convergence ability and prediction accuracy. For example, reference [30] utilized an improved ant lion algorithm to optimize the weights and thresholds of the BP neural network, improving its prediction accuracy.

The remaining part of the article is expanded as follows: Section 2 determines the evaluation indicators for power system risks; The third section uses the comprehensive weight allocation method to assign weights to the indicators; Section 4 establishes a power system risk assessment and prediction model based on IACO and BP neural network; Finally, Section 5 summarizes the article and proposes future development directions.

2 Risk assessment indicators for power system

In order to quantitatively evaluate and warn of power system risks, it is necessary to select key indicators that have a significant impact on power system risks for analysis. When selecting corresponding indicators, full consideration should be given to multiple factors in the actual operation of the power system, in order to improve the accuracy, objectivity, and comprehensiveness of the risk assessment model.

2.1 Principles for selecting indicators

With the continuous expansion of the scale of the power system and the complexity of its internal structure, it is difficult to directly obtain or the process of obtaining data related to some power system risks is extremely cumbersome. Therefore, when establishing a risk assessment and early warning model for the power system, in order to ensure scientificty, effectiveness, and standardization, the process of selecting indicators should follow the following principles:

1. Principle of logic

The principle of logicality refers to the inherent logical relationship between the selected indicators and risk types when selecting key indicators to evaluate the risks in the operation process of the power system. On the other hand, the selected indicator set should have the ability to fully reflect power system risk related information and inducing factors from different dimensions.

2. Principle of directionality

When constructing an evaluation model for evaluating power system risks, it is necessary to take multidimensional factors such as specific work scenarios, load characteristics, and power supply environment as the basis, emphasizing the pertinence of the selected indicators for the evaluation object. In fact, a comprehensive evaluation model designed for a specific object can only be used for performance evaluation and prediction of that object. When the object changes, targeted adjustments should be made.

3. Principle of convenient operation

Convenient operability is an important feature of constructing power system risk assessment models, which is related to the accuracy and credibility of data samples. When selecting indicators, full consideration should be given to the difficulty and cost of obtaining indicator data. The real data of some indicators is difficult to obtain in actual working environments, which can have an impact on the risk assessment model of the power system.

4. Principle of efficiency

In the current production environment, complex substation equipment systems require high response speed and computational power for corresponding risk assessment models. When constructing the corresponding evaluation system, the principle of convenience should be emphasized. Utilize existing data processing algorithms to reduce computational burden and accelerate model response speed.

2.2 Evaluation indicators

Consider the main impacts of distribution network power supply reliability, power supply
capacity, power quality, and network structure. The following indicators are selected to construct a risk assessment model.

<table>
<thead>
<tr>
<th>Primary indicators</th>
<th>Indicator number</th>
<th>Secondary index</th>
<th>Indicator number</th>
<th>Indicator meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power supply</td>
<td>A</td>
<td>Equipment failure rate</td>
<td>A1</td>
<td>The rate of faults occurring in power supply equipment per unit time</td>
</tr>
<tr>
<td>reliability</td>
<td></td>
<td>Average interruption hours of customer</td>
<td>A2</td>
<td>The product of power outage duration and the number of power outage users divided by the total number of users</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average number of power outage users</td>
<td>A3</td>
<td>Number of power outages by the user during the sampling period</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Old equipment rate</td>
<td>A4</td>
<td>Equipment ratio with operating time greater than 30 years</td>
</tr>
<tr>
<td>Power supply</td>
<td>B</td>
<td>Power capacity rate</td>
<td>B1</td>
<td>The ratio of distribution network transformation capacity to corresponding load</td>
</tr>
<tr>
<td>capacity</td>
<td></td>
<td>Line overload ratio</td>
<td>B2</td>
<td>The ratio of line overload operating time to total operating time</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Supply and storage ratio</td>
<td>B3</td>
<td>The absorption capacity of intermittent energy in the distribution network</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Consumption ratio</td>
<td>B4</td>
<td>The utilization rate of intermittent energy in the distribution network</td>
</tr>
<tr>
<td>Electrical</td>
<td>C</td>
<td>Three-phase unbalance</td>
<td>C1</td>
<td>The amplitude of three-phase current and voltage is inconsistent and does not comply with regulations</td>
</tr>
<tr>
<td>energy quality</td>
<td></td>
<td>Nonlinear load rate</td>
<td>C2</td>
<td>Distortion of voltage or current sine waves</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Impact load rate</td>
<td>C3</td>
<td>Frequency and voltage fluctuations when the amplitude of change is greater than the system capacitance</td>
</tr>
<tr>
<td>Grid structure</td>
<td>D</td>
<td>Average qualified rate of Grid connected node voltage</td>
<td>C4</td>
<td>Voltage qualification of distributed energy grid connected nodes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average qualified rate of grid connected node current</td>
<td>C5</td>
<td>Current qualification of distributed energy grid connected nodes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grid interconnection rate</td>
<td>D1</td>
<td>The ratio of lines with interconnection switches to the total length of the line</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average power supply radius</td>
<td>D2</td>
<td>The average length of the wire from the transformer to the user</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Insulation rate</td>
<td>D3</td>
<td>The ratio of cables and insulated overhead lines to the total length of the line</td>
</tr>
<tr>
<td></td>
<td></td>
<td>line loss rate</td>
<td>D4</td>
<td>Percentage of line loss load and power supply load</td>
</tr>
</tbody>
</table>

3 Index weight allocation and comprehensive evaluation

After determining the power system risk assessment indicators shown in Tab.1, it is necessary to allocate weights based on the impact characteristics of each indicator on power system risk in the actual system. AHP is a decision analysis method that determines the relative importance of multiple indicators or factors in the overall hierarchy by comparing and analyzing them. AHP has the advantages of simple structure and convenient operation, making it widely used. However, AHP has subjectivity in determining the hierarchical structure and determining the
importance of indicators, and is not suitable for designing complex decision-making problems with many factors. Therefore, the article utilizes AHP and EWM to jointly allocate weights to the indicators of the power system risk assessment model, considering both subjective and objective factors to improve the accuracy and credibility of the results.

3.1 AHP

The commonly used approach to determine the weight of evaluation indicators using the AHP method is to decompose the research object into multiple independent sub factors. Based on the internal coupling characteristics between different sub factors, a multi-level evaluation model is established by combining them according to the hierarchical division. Establish the following discriminant matrix \( A = (a_{ij})_{n \times n} \) using the three-scale method

\[
A = \begin{bmatrix}
a_{11} & a_{12} & \cdots & a_{1n} \\
a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{n1} & a_{n2} & \cdots & a_{nn}
\end{bmatrix}
\]  

where \( a_{ij} (i, j = 1, 2, L, n) \) is used to represent the importance of \( a_i \) relative to \( a_j \). Determine importance indicators by comparing multiple factors in pairs. When \( a_{ij} \) takes a value of 1, it indicates that \( a_i \) is more important than \( a_j \), and vice versa, it indicates that \( a_j \) is more important than \( a_i \).

After determining the discriminant matrix, determine the optimal transfer matrix \( L \) for the above discriminant matrix \( A \):

\[
L = \begin{bmatrix}
l_{11} & l_{12} & \cdots & l_{1n} \\
l_{21} & l_{22} & \cdots & l_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
l_{n1} & l_{n2} & \cdots & l_{nn}
\end{bmatrix}
\]  

The relationship between the corresponding elements in the transmission matrix and the corresponding elements in the discrimination matrix \( A \) satisfies the following equation:

\[
l_{ij} = \frac{1}{n} \sum_{i=1}^{n} a_{ii} + a_{ij}
\]  

In addition, the optimal consistency matrix \( X \) of the optimal transfer matrix \( L \) can be expressed as:

\[
X = \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1n} \\
x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{n1} & x_{n2} & \cdots & x_{nn}
\end{bmatrix}
\]  

where \( x_{ij} \) can be determined by \( x_{ij} = \exp(l_{ij}) \).

Calculate the geometric mean value of elements in the discrimination matrix \( A \) by the following formula:

\[
b_i = \left( \prod_{j=1}^{n} a_{ij} \right)^\frac{1}{n}, \quad i = 1, 2, L, n
\]  

Normalizing the \( b_i (i = 1, 2, L, n) \) obtained from Eq.(5) can determine the weight \( \omega_{i-AHP} \) of each indicator in the AHP method, which can be expressed as:

\[
\omega_{i-AHP} = \frac{b_i}{\sum_{i=1}^{n} \left( \prod_{j=1}^{n} a_{ij} \right)^\frac{1}{n}}, \quad i = 1, 2, L, n
\]  

3.2 Entropy weight method

Unlike the principle of AHP using subjective experience to weight indicators, EWM is a weighting method that starts from objective factors. In the practical application process, it is mainly based on the information entropy to calculate the index entropy weight of different influence degrees, and then the entropy weight is used to process each index to get the result. Assuming that the evaluation matrix of the power system risk assessment model is \( X = [x_{ij}] \), and when calculating the indicator weight using the EWM method, the weight ratio \( P(x_j) \) of \( j \) under indicator \( x_j \) can be expressed as:

\[
P(x_j) = \frac{x_j}{\sum_j x_j}
\]  

The entropy value \( e_j \) of indicator \( j \) can be expressed as:

\[
e_j = -\sum P(x_j) \ln(P(x_j))
\]
Therefore, the entropy weight of the indicator $j$ is defined as:

$$\omega_{j-en} = \frac{1 - e_j}{q - \sum_{j'=1}^{q} e_{j'}}$$  \hspace{1cm} (9)$$

where $e_j$ is the entropy value of indicator $j$.

Considering the impact of different factors on the collected data of each indicator, such as data loss and pollution, the weights of the evaluation indicators are normalized:

$$C_i' = \frac{C_i^n}{\sum_{i=1}^{m} C_i}$$ \hspace{1cm} (10)$$

where $C_i'$ and $C_i^n$ represent the normalized weight value and initial weight value of evaluation indicator $i$, respectively; $m$ and $C_i$ represent the adjusted number of indicators and evaluation indicator $i$, respectively.

### 3.3 Comprehensive weight allocation

For the power system risk assessment model, some risk factors largely depend on the operational experience of technical personnel in the past power system repair and maintenance processes. When establishing a comprehensive assessment model for power system risk, emphasis should be placed on considering the weight proportion determined based on human experience, and increasing the proportion of the weight obtained by the AHP method in the total weight. Therefore, the final weight $\omega_k$ of each evaluation indicator is:

$$\omega_k = 0.65\omega_{k-AHP} + 0.35\omega_{k-en}$$ \hspace{1cm} (11)$$

where $\omega_{k-AHP}$ represents the weight value of the indicator $k$ under the AHP method; $\omega_{k-en}$ represents the weight value of the above indicators under the entropy weight method.

Summarize the above analysis and use AHP and EWM to comprehensively assign weights to various indicators of the power system risk assessment model. The weight allocation results of each primary indicator and corresponding secondary indicators are shown in Tab.2.

### Tab.2 Indicator selection results of power system risk assessment model

<table>
<thead>
<tr>
<th>Primary indicators</th>
<th>Weight</th>
<th>Secondary indicators</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.3247</td>
<td>A1</td>
<td>0.3325</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>0.1742</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A3</td>
<td>0.2069</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A4</td>
<td>0.2864</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B1</td>
<td>0.1463</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B2</td>
<td>0.2844</td>
</tr>
<tr>
<td>B</td>
<td>0.3056</td>
<td>B3</td>
<td>0.1975</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B4</td>
<td>0.3718</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C1</td>
<td>0.2312</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C2</td>
<td>0.1430</td>
</tr>
<tr>
<td>C</td>
<td>0.1943</td>
<td>C3</td>
<td>0.1713</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C4</td>
<td>0.2931</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C5</td>
<td>0.1614</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D1</td>
<td>0.2454</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D2</td>
<td>0.2968</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D3</td>
<td>0.1524</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D4</td>
<td>0.3054</td>
</tr>
</tbody>
</table>

### 3.4 Risk assessment of power system

After determining the comprehensive weights of various indicators in the power system risk assessment model based on the above analysis, the multiple regression analysis algorithm is used to calculate the corresponding scoring values for
different data. Use the following regression equation to describe the relationship between evaluation indicators and scores:

\[ Q = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \]  

In the formula, \( Q \) represents the scoring value corresponding to the evaluation indicator data; \( \beta_i \) \((i = 1, 2, \ldots, n)\) represents the regression coefficient; \( x_i \) \((i = 1, 2, \ldots, n)\) represents the independent variable; \( \varepsilon \) represents the random error distribution term, satisfying \( \varepsilon \sim N(0, \sigma^2) \).

When using multiple regression equations to evaluate the risk of the distribution network power system, it is necessary to determine the corresponding samples of the evaluation indicators through independent tests to estimate the regression coefficient \( \beta_i \) \((i = 1, 2, \ldots, n)\) mentioned above:

\[
\begin{align*}
Q_1 &= \beta_0 + \beta_{11} x_{11} + \beta_{21} x_{21} + \ldots + \beta_{p1} x_{p1} + \varepsilon_1 \\
Q_2 &= \beta_0 + \beta_{12} x_{12} + \beta_{22} x_{22} + \ldots + \beta_{p2} x_{p2} + \varepsilon_2 \\
Q_n &= \beta_0 + \beta_{1n} x_{1n} + \beta_{2n} x_{2n} + \ldots + \beta_{pn} x_{pn} + \varepsilon_n
\end{align*}
\]  

4 Autonomous Risk Assessment and Early Warning Strategy for Power System

After weighting the selected indicators according to the weight comprehensive allocation strategy of power system risk indicators established in Section 3, the corresponding indicator values and comprehensive risk assessment results for each power system can be determined through multiple regression equations. By using the corresponding relationships between multiple sets of power system indicator data and comprehensive evaluation results as samples to train BP neural networks, the adaptive advantages of neural networks can be utilized to analyze the complex nonlinear relationship between data and risk, achieving autonomous assessment and early warning of power system risks. The idea of the power system risk independent assessment and early warning strategy designed in the article is shown in Fig.1.
4.1 Improved Ant Colony Optimization Algorithm

When ant colony algorithm optimizes and solves complex nonlinear problems, it draws inspiration from the natural thinking of ants foraging. When ants pass a certain road, they will release pheromone, which will guide the follow-up ants to move towards the direction of higher pheromone concentration. On this basis, the large-scale movement of ant colony can form a positive feedback mechanism about pheromone. The path with less pheromone accumulation will eventually disappear with the decrease of ants and the dissipation of pheromone. Based on the path search and optimization of the ant colony, the optimal path can be determined.

In the process of finding the optimal solution, the ants determine the subsequent path by sensing the pheromone concentration. Therefore, the pheromone in the ant colony algorithm plays a vital role in the overall performance of the algorithm. The traditional ant colony algorithm only has the global pheromone update method, that is, the pheromone on the path is only updated in the iterative process. This update method not only affects the search speed of the algorithm, but may also lead to the algorithm falling into a local optimal solution. In order to avoid the above shortcomings, the pheromone update method with adaptive volatility coefficient and the best worst reward and punishment mechanism are used to iterate the pheromone update to improve the pheromone update strategy of the ant colony algorithm.

According to the above analysis, the updating formula of pheromone with adaptive volatility coefficient proposed in the article can be expressed as:

$$\tau_{ij}(t) = (1 - \rho)\tau_{ij}(t-1) + \rho \tau_0$$  \hspace{1cm} (14)

where $\tau_{ij}$ represents the pheromone between node $i$ and node $j$; $\rho$ represents the adaptive volatilization factor of pheromone.

The adaptive volatilization factor is designed as:

$$\rho = \rho_{\text{start}} \left(1 - \frac{NC - 1}{NC_{\text{max}}}\right)$$  \hspace{1cm} (15)

where $\rho_{\text{start}}$ represents the initial value set during the initialization phase; $NC$ represents the number of cycles; $NC_{\text{max}}$ is the maximum number of cycles.

The global pheromone update formula including reward mechanism can be expressed as:

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \rho \left(\Delta \tau_{ij}^\text{best}(t) + \Delta \tau_{ij}^\text{worst}(t) - \Delta \tau_{ij}^t(t)\right)$$  \hspace{1cm} (16)

In the above global pheromone update formula, there are:

$$\Delta \tau_{ij}^\text{best}(t) = \begin{cases} \frac{Q}{L_{\text{best}}}, & (k_i \rightarrow k_j) \in \text{optimal path} \\ 0, & \text{others} \end{cases}$$  \hspace{1cm} (17)

$$\Delta \tau_{ij}^\text{worst}(t) = \begin{cases} \frac{Q}{L_{\text{worst}}}, & (k_i \rightarrow k_j) \in \text{optimal path} \\ 0, & \text{others} \end{cases}$$  \hspace{1cm} (18)

where $\Delta \tau_{ij}^t(t)$ represents the pheromone left by ant $k$ between node $i$ and node $j$ in the process of iteration $t$.

According to the above local pheromone update and the best worst reward and punishment mechanism iteration pheromone formula, the ant colony optimization algorithm can be improved to improve the optimization performance of the algorithm.

4.2 Risk assessment strategy based on BP neural network

BP neural network is a feedforward network that transmits signals forward and errors backward. It is commonly used for predicting uncertain systems and has the advantages of strong learning ability and high prediction accuracy. The structure of the BP neural network is shown in Fig.2.
In order to improve the fitting ability of BP neural network, sigmoid function is used as the activation function. The loss function selects the cross-entropy function to measure the difference between the output value and the true value of the BP neural network:

$$\text{Loss} = - \sum_{i=1}^{n} T_r \ln \left( \frac{T_r}{D_r} \right) + (1-T_r) \ln \left( \frac{1-T_r}{1-D_r} \right)$$

where $T_r$ and $D_r$ represent the target and actual values of the BP neural network, respectively; $n$ represents the number of output nodes.

Although the traditional BP neural network model has good performance when applied to nonlinear system prediction, there are still some problems such as slow convergence speed and easy to fall into local optimization. The development of swarm intelligence algorithm provides a new idea for improving the prediction performance of BP neural network. Based on this, when determining the weight and threshold parameters of the BP neural network, the article uses an improved ant colony optimization algorithm to make optimization decisions. In addition, the mutation factor is introduced in the above optimization process to obtain the optimal weight and threshold combination of the BP neural network in the current scenario.

The specific steps to determine the optimal weight and threshold of the BP neural network using ant colony optimization algorithm are as follows:

1. Initialize ant colony parameters. Set the number of ants in optimization as $m$, the initial pheromone of the elements contained in the set as $C$, and the maximum number of iterations in the optimization process as $N_{max}$.

2. In each optimization step, start all ants for optimization. For ant $k$, the probability of the selected ant element $j$ is determined according to the pheromone concentration value of each element. Adopt the roulette theory random selection probability as described in the following equation:

$$P(I_j) = \frac{[\tau_j(I_j)]^\alpha [\eta_j(I_j)]^\beta}{\sum_{i=1}^n [\tau_i(I_i)]^\alpha [\eta_i(I_i)]^\beta}$$

where $\tau_j(I_j)$ represents the pheromone concentration of the ant element; $\eta_j(I_j)$ represents the visibility of the ant element; $\tau_i(I_i)$ represents the pheromone concentration of the ant element; $\eta_i(I_i)$ represents the visibility of the ant element.

3. During the optimization process, all ants select elements and are considered to have found food. Establish a BP neural network model based on the element selection characteristics of ants, and input the optimized training data. Calculate the function value according to Eq.(19) to represent the path traveled by each ant.

4. Select ants with the shortest path distance to return to the starting point along the original route, and update its pheromone at the same time. The time experienced by ants is $a$. The ant's pheromone concentration is updated according to the designed pheromone updating method including adaptive volatility coefficient and the optimal worst reward and punishment mechanism iterative pheromone formula.

5. Repeat steps (2) - (4) until all ants in the optimization process converge to the same path or reach the maximum number of iterations.

4.3 Results and analysis

The risk assessment of the power system should have real-time and accurate characteristics. Based on this, this article uses BP neural network to achieve independent risk assessment of specific
power systems under indicator data, improving assessment accuracy while reducing the time consumption of the calculation process. When simulating and testing the proposed research idea in MATLAB software, taking the actual operation data of a certain city's power system as an example, after removing incomplete and defective data, a total of 700 sets of data were finally obtained as sample data for BP neural network training and testing. The type of data matrix is the corresponding values of each indicator and the comprehensive evaluation results, with a dimension of 17*701. During simulation, set the number of input layer nodes to 17 and the number of output layer nodes to 1. In addition, assuming that the comprehensive score of power system risk is determined using multiple regression analysis algorithm (with a score distribution interval of [0,100]), the score is divided into four intervals as shown in Tab.3 to describe the actual working conditions of the power system.

<table>
<thead>
<tr>
<th>Risk level</th>
<th>Scoring range</th>
<th>Number</th>
<th>Operation suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0-20</td>
<td>1</td>
<td>No action required, continue running</td>
</tr>
<tr>
<td>Medium</td>
<td>20-30</td>
<td>2</td>
<td>Maintain according to regulations</td>
</tr>
<tr>
<td>Attention</td>
<td>30-40</td>
<td>3</td>
<td>Real-time monitor</td>
</tr>
<tr>
<td>Abnormal</td>
<td>40-100</td>
<td>4</td>
<td>Immediate repair</td>
</tr>
</tbody>
</table>

Select 650 sets of data from the identified data samples as training samples for the BP neural network. To avoid the subjectivity of manually selecting data during the training of neural networks, the process of selecting training samples is completed using random functions. The remaining 50 sets of data are used for risk assessment accuracy testing of the BP neural network model.

In fact, the more nodes in the hidden layer, the better. A relatively large number of hidden layer neurons will seriously increase the computational burden and reduce the overall prediction performance. The number of hidden layer nodes is determined according to the following empirical formula:

$$ l = a + \sqrt{m + n} \quad (a \in [1,10]) $$

\[ (21) \]

where $m$ and $n$ represent the number of nodes in the input layer and output layer, respectively; $a$ represents a random integer; $l$ represents the number of nodes in the hidden layer, and after calculation, its range is determined to be [6,14].

When determining the number of hidden layer nodes, the equality coefficient described in the following equation can be used as the evaluation indicator. The closer this value is to 1, the better the predictive performance of the BP neural network under the number of nodes in this hidden layer:

$$ E = 1 - \frac{\sqrt{\sum_{i=1}^{n} (y_i - y^*_i)^2}}{\sqrt{\sum_{i=1}^{n} (y_i)^2} + \sqrt{\sum_{i=1}^{n} (y^*_i)^2}} \quad (22) $$

where $n$ represents the total number of predicted samples; $y_i$ and $y^*_i$ represent actual and predicted values, respectively.

According to Eq.(22), calculate the data accuracy of the proposed key secondary equipment fault prediction algorithm during training when the number of hidden layer nodes changes, as shown in Fig.3. According to the variation curve of prediction accuracy corresponding to different hidden layer nodes shown in Fig.3, when the number of hidden layer nodes is 10, the BP neural network model has the highest prediction accuracy. Therefore, the number of hidden layer neurons in the BP neural network selected for power system risk assessment is 10.

$$ X = \frac{N_{\text{right}}}{N_{\text{total}}} \times 100\% \quad (23) $$

where $X$ represents the prediction accuracy of the BP neural network; $N_{\text{right}}$ and $N_{\text{total}}$ represent the number of correctly predicted samples and the total number of samples, respectively.
After the training of the power system risk assessment model based on BP neural network is completed, the accuracy of the trained BP neural network is tested using the remaining 50 sets of data. The test results are shown in Fig. 4. According to Fig. 4 (a), the research idea proposed in this paper to use IACO algorithm to global optimization the weights and thresholds of BP neural network for power system risk assessment is effective. Among the 50 sets of sample data used to test the prediction accuracy of the BP neural network, the error between the predicted results and the actual results corresponding to the sample data is relatively small. In addition, according to Fig. 4 (b), the predicted risk levels corresponding to Tab. 3 obtained from the proposed power system risk assessment and warning strategy are almost identical to the actual risk interval corresponding to the data. Among all 50 sets of data, only one set of predicted results did not match the actual results. From the perspective of risk distribution level prediction, the proposed BP neural network based on IACO optimization has a prediction accuracy of 98%. Therefore, this model can effectively and accurately predict the actual working state of the power system, and has good application prospects.

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**Fig. 3** Prediction accuracy when the number of hidden layer nodes changes

<table>
<thead>
<tr>
<th>Node number</th>
<th>Prediction accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>90</td>
</tr>
<tr>
<td>8</td>
<td>95</td>
</tr>
<tr>
<td>10</td>
<td>95</td>
</tr>
<tr>
<td>12</td>
<td>90</td>
</tr>
<tr>
<td>14</td>
<td>85</td>
</tr>
</tbody>
</table>

The number of nodes corresponding to the highest prediction accuracy serves as the number of neurons in the hidden layer.
Fig. 4 Test results and interval distribution of BP neural network

Afterwards, in order to verify the impact of the proposed method of using IACO to optimize the weights and thresholds of the BP neural network on the prediction accuracy of the BP neural network, the article randomly selected 5 sets of data from the above 700 sets for testing, and the results are shown in Fig. 5. According to Fig. 5, IACO can improve the prediction accuracy of BP neural networks by adjusting their weights and thresholds, resulting in smaller prediction errors than traditional BP neural networks. When not optimized by IACO, the prediction accuracy of traditional BP neural networks is relatively low, with one of the five sets of test data experiencing incorrect predictions (Fig. 5 (b)).

Fig. 5 Test results of the optimization effect of IACO on BP Neural Network

5 Conclusion

In order to reduce the adverse impact of potential risks in the power system on normal power supply, the article proposes a power system risk assessment and warning strategy based on IACO and BP neural network. The main conclusions of the article are as follows:

1. The combination method of AHP and EWM is used to comprehensively assign weights to indicators that have a significant impact on the stability and safety of power system operation, achieving a balanced consideration of subjective experience and objective factors, and improving the credibility of evaluation results. Afterwards, multiple regression analysis is used to calculate the risk assessment results of the selected indicators and weights corresponding to the power system.

2. According to the above weight allocation process, training and testing samples for the BP neural network were calculated and obtained. At the same time, IACO is used to global optimization the weights and thresholds of BP neural network, which improves the convergence ability and prediction accuracy of BP neural network.

3. The test results validate the effectiveness and accuracy of the proposed risk assessment and warning strategy for power systems using IACO and BP neural networks, which can significantly improve power supply quality and have significant application prospects.

In future research, we will continue to study high-performance prediction algorithms to further obtain a power system risk warning mechanism with simple calculation and high accuracy.

Reference


