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Fault Risk Assessment of Transmission Lines Under Extreme Weather Conditions Based on Genetic Algorithm Back-Propagation Neural Network

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Abstract: In the context of global climate change environment, China's power grid is faced with many extreme weather challenges, especially the southern China power grid region, which faces typhoons, torrential rain, high temperature, drought, frost and other disasters that greatly affect the safe and stable operation of the power system and the normal social order in this region. This study proposes a risk assessment model combining a genetic algorithm-optimized neural network (GA-BP) with GIS spatial analysis to evaluate transmission line faults under extreme weather in southern China. Experimental results demonstrate the model's effectiveness in identifying high-risk regions, with significant correlations between extreme precipitation, prolonged drought, and circuit failures.

Keywords: extreme weather disasters; GA-BP; transmission line fault prediction; risk assessment

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1. Introduction

With the rapid development of China's economy, the demand for electric power energy is increasing. As an important carrier of electric power transmission, transmission lines' safe and stable operation is very important. However, China has a vast territory as well as a complex and diverse climate, and dangerous meteorological phenomena occur frequently, which have serious impacts on transmission lines and bring great challenges to the power supply. In July 2021, the city of Zhengzhou in China's Henan province was hit by unusually heavy rains, resulting in severe urban waterlogging and power circuit failures. The rainstorm caused the power grid to almost collapse, leading to a large area of power outages and seriously affecting residents' lives and city operations. In July 2021, Typhoon Firework made landfall in China's Guangdong Province, bringing strong winds and heavy rain, causing severe damage to power facilities and widespread power outages, and affecting the lives of millions of people. Therefore, in view of such weather disasters, it is urgent to systematically and scientifically study the power system. In view of the challenges and problems faced by extreme weather conditions, an extreme weather boundary prediction model is established, and the risk identification technology of power circuit failure under extreme weather is studied, which is helpful to identify the potential vulnerability and risk points of the power grid and improve its reliability, resilience and emergency response ability.

To date, the research on the impact of extreme weather events on transmission lines has focused on the spatial and temporal distribution characteristics of extreme meteorological disasters and the risk assessment of meteorological disasters.

Dr. Chen Lizheng focused on the risk assessment of extreme weather events for power systems [1]. By constructing corresponding evaluation models and methods, the risks that each link of the power system may face under extreme meteorological conditions are discussed in depth. Wang Jie et al. focused on the northern Hebei Power Grid and analyzed the distribution characteristics of its disaster accidents in time and space dimensions [2]. After collecting the historical data of disaster events related to the northern Hebei Power Grid, statistical analysis and other methods were used to summarize the frequency and intensity of disaster-related incidents in different time periods and different regions. However, this method has limitations in data collection, such as incomplete data in special complex terrain, and insufficient accuracy of some data. Deng Honglei, Dai Dong and Li Shuwen [3] adopted the AHP and entropy weight group method to carry out a comprehensive operation risk assessment of overhead transmission lines. Wang Jian [4] carried out in-depth analysis of the risk of transmission lines affected by meteorological disasters, focusing on exploring early warning methods. The various types of meteorological disasters (such as lightning, wind, ice cover, etc. [5]) affecting transmission lines, the damage forms and risk evolution rules that the lines may suffer in terms of structural safety and electrical performance were analyzed in detail, and the correlation between geo-meteorological factors and transmission line risks was examined in order to construct risk assessment indicators that can reflect geo-meteorological correlations [6]. Specific quantitative calculations are used to measure the risk differences faced by transmission lines in different regions [7]. However, most of the studies have regional or landscape specificity; thus, the results are not universally applicable to different geographical climates and power grid structure regions and it is difficult to cover all line types and complex terrain conditions.

In addition, some researchers have used geographical models to build power grid meteorological disaster warning models. The author of [8] combined the geographical location information of power grid facilities with meteorological data, fully considering the effects of terrain, landform and other geographical factors on the spread, impact scope and intensity of meteorological disasters, and established appropriate mathematical models and algorithms. It enables predictions and early warnings to be made concerning the region, time and proportion of the power grid that may suffer from meteorological disasters. However, due to the limited dynamic adaptability of the model, it is difficult to adjust in time with the development of the power system and the long-term changes in geography and meteorology. The range of model validation is limited, and there are errors in index quantization, as well as problems such as mismatches between different models which affect the application effectiveness [9–11].

In summary, it can be seen that the current domestic research on the impact of extreme meteorological disasters on transmission lines has the following problems:

The first is the scope of application. The above studies mostly focus on specific areas or some typical situations and have limited universality, which means that improvements to make them more widely applicable are necessary. At present, the domestic research on the regional scenarios of the China Southern Power Grid is insufficient and cannot provide targeted auxiliary decision-making functions for this power grid region. Therefore, it is necessary to study the correlation impact of extreme weather on transmission lines in the five provinces of the Southern Power Grid [12].

Second, there are limitations in data acquisition, such as difficult data collection in extreme cases and local areas, and insufficient consideration of climate change.

Third, the adaptability and accuracy of relevant models and methods are not good in the face of complex terrain and geomorphology and unexpected situations [13].

The fourth is the quantification of indicators and model accuracy. Some evaluation indicators have errors in quantification, and model construction is limited by the accuracy of geographical and meteorological models, which affects the accuracy and reliability of research results [14,15].

Previous studies have tended to use statistical methods to assess the impact of extreme weather on power grids. In this study, neural network technology is combined with GIS spatial analysis to solve the above limitations. Meteorological data from observation stations and transmission line fault records in southern China were integrated to establish the model [16].

2. Materials and Methods

2.1. Research Methods

In this research, a GA-BP neural network model is proposed to construct a correlation model between extreme weather characteristics and circuit faults. In combination with the current research on extreme weather events, feature indices are selected, circuit fault data under different voltages are collected in the southern grid region, and extreme weather characteristics covering a large area of China Southern Power Grid and transmission line fault conditions are input to predict circuit fault data in different regions [17,18]. The global weight importance evaluation method of the neural network is used to output the influence weights of different extreme weather indicators on circuit faults [19–21]. Using a GIS spatial analysis method, the extreme weather index layer attribute value is superimposed according to the weight, and the circuit fault risk level index is obtained. The spatial and temporal boundary of extreme weather risk is divided into five risk regions: low, lower, medium, higher, and high. Risk levels are classified using standard deviation thresholds: low ($\mu < 0.1$), lower ($0.1 \leq \mu < 0.35$), medium ($0.35 \leq \mu < 0.65$), higher ($0.65 \leq \mu < 0.9$), and high ($\mu \geq 0.9$). (μ represents the normalized risk index).

This study collected circuit fault data for 2021, 2022 and 2023, and the average number of faults at different voltages (10 kv, 35 kv, 110 kv, 220 kv and 550 kv) per year was roughly 120,000, 8000, 3000, 900 and 350.

The schematic diagram of the entire process of risk assessment of extreme weather effects on power grid faults based on the GA-BP network model is outlined in Figure 1 below.

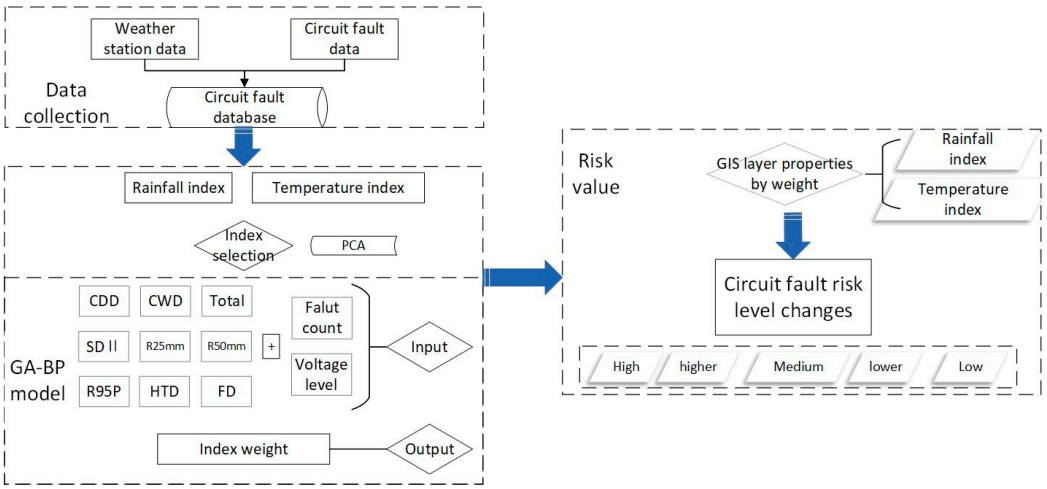

Figure 1. Based on the GA-BP fault risk level technical roadmap.

In terms of obtaining and processing fault data, we first obtained the location information, the number of faults and the corresponding fault voltage of each fault area in the research area, also recording the time and type of faults. The processed extreme weather indicator data and power fault data were spatially correlated and matched.

2.1.1. Establishment of Extreme Weather Risk Assessment Model

Based on the risk theory of extreme weather disasters, a flood disaster is a complex system composed of disaster-causing factors, a disaster-bearing environment, disaster-bearing bodies and flood control and disaster reduction capabilities [22,23]. This paper conducts an extreme weather risk assessment for the Southern Power Grid region, carrying out a comprehensive assessment of extreme weather disaster risks and examining the risk of extreme rainfall and extreme temperature as disaster-causing factors.

The disaster risk assessment model can be expressed by the following calculation formula:

$$F = W_{H1}X_{H1} + W_{H2}X_{H2} + \cdots + W_{Hi}X_{Hi} \quad (1)$$

In the formula, F is the extreme weather disaster risk index, which is used to represent the risk degree. The greater the value, the greater the disaster risk degree is. W_{Hi} represents the weight value of the disaster risk index in the extreme meteorological disaster risk assessment model. X_{Hi} is the standardized value of each evaluation index.

The extreme weather disaster risk index method is mainly based on the differences in the raster data of the transmission line risk evaluation results of extreme disasters in different research periods. The raster computer in the geographic information software Arcmap is used to calculate the raster data of risk evaluation in different research periods and obtain the risk index change distribution map.

2.1.2. Selection of Extreme Weather Characteristic Indicators

Extreme weather events exist in sharp contrast to average weather events. Beniston and his team identified three criteria that define extreme weather events: low frequency of events; serious social and economic losses; and a relatively small or large strength value. In the third and fourth assessment reports of the IPCC, extreme climate events are clearly defined from the dimensions of the probability distribution, that is, for a specific place and time, extreme climate events are events with a very low probability of occurrence, and their occurrence probability usually only accounts for 10% or less of similar climate events. This definition is concise and precise, and fully takes into account the differences in climate in different regions.

Different scholars have adopted different thresholds to define extreme climate events according to the characteristics of specific research areas they focus on. For example, Zhai Panmao et al. [12,13] analyzed the change characteristics of extreme precipitation in China in 1999 through the maximum 1-day precipitation, maximum 3-day precipitation, precipitation events with daily precipitation greater than or equal to 50 mm, and precipitation events with daily precipitation greater than or equal to 100 mm. Yu Fangyuan [14] evaluated the changes in extreme climate precipitation in northeast China in 2011 by using extreme precipitation (the precipitation at the sub-points where the daily precipitation exceeded 90%), precipitation intensity, maximum 5-day precipitation, and the longest consecutive dry days. In 2010, Wang Fang and Tian Hong used extreme rainfall (daily rainfall greater than 95% of the points of rainfall), extreme precipitation frequency, and extreme precipitation intensity to judge the change in extreme precipitation in the Huaihe River Basin. In terms of assessing extreme temperature events, Mutiibwa et al. used warm-day days (days with daily maximum temperatures greater than the 90% threshold) and cold-night days (days with daily minimum temperatures below the 10% threshold) to assess changes in extreme

temperatures in the continental United States in 2015. Zhai Panmao and Pan Xiaohua used the number of high-temperature days (maximum temperature greater than 35 °C), the number of frost days (minimum temperature lower than 0 °C) and the number of low-temperature days to evaluate the changes in extreme temperature events in northern China in 2003. In 2005, Tang Yuhong used the maximum temperature, minimum temperature and daily temperature range to evaluate the characteristics of extreme temperature changes in China [24].

To date, some scientific institutions have built an index system for evaluating extreme weather events. For example, the European Meteorological Office (ECA) has developed a set of indices for describing extreme weather events. The Panel of Experts on Climate Change Detection and Extreme Climate Event Indicators (ETCCDI) of the International Intergovernmental Conference on Climate Change (IPCC) has determined a set of extreme indices including temperature indices and precipitation indices, among which the extreme climate index defined by ETCCDI is very representative [25]. These widely recognized indices have brought great convenience to the study of extreme climate change and have been widely used by many researchers in China and elsewhere [16].

Combined with the above studies on extreme weather indicators by many researchers, this study uses the principal component analysis method to screen out the following extreme weather characteristic indicators as inputs to the neural network model: maximum continuous dry days (CDD), maximum continuous wet days (CWD), total annual precipitation, average annual precipitation intensity (SDII), heavy precipitation days (R25 mm and R50 mm), heavy precipitation rate (R95p), high-temperature days (HTD), and frost days (FD). The characteristics of extreme weather are defined below:

Maximum consecutive dry days (CDD): The maximum number of consecutive days without precipitation in a year.

Maximum consecutive wet days (CWD): The maximum number of consecutive days with precipitation in a year.

Total annual precipitation: The total amount of precipitation in a year.

Average annual precipitation intensity (SDII): The ratio of total annual precipitation to wet days (days with daily precipitation greater than 1 mm).

Heavy precipitation days (R25 mm and R50 mm): Days when the daily precipitation is greater than or equal to 25 mm and 50 mm.

Heavy precipitation rate (R95p): The ratio of annual cumulative precipitation to total annual precipitation when the daily precipitation is greater than 95% of the quantile value.

High-temperature days (HTD): The number of days in the year with a maximum daily temperature of 35 degrees Celsius or higher.

Frost days (FD): The number of days in the year with a minimum daily temperature of 0 °C or less.

2.2. Establishment of Power Grid Fault Risk Grade Evaluation Model Based on GA-BP Neural Network

The role of the GA-BP network model is to give the influence weights of different extreme weather characteristic index on circuit faults. Figure 2 shows the GA-BP neural network model. The GA-BP framework was selected for its ability to optimize hyperparameters globally (via genetic algorithms) and refine weights locally (via backpropagation), which is particularly effective in handling nonlinear relationships between high-dimensional meteorological features and fault risks [26].

According to the current research methods for investigating extreme weather events, this research obtained the observation data of extreme weather and the methods of calculating and studying extreme weather of conventional meteorological observation stations. Data and statistics for national meteorological observation stations and meteorological

bureaus in the target research area were obtained for the years studied. These data include hourly rainfall, hourly average temperature, hourly maximum temperature, hourly minimum temperature, hourly maximum wind speed, instantaneous wind speed, and average wind speed. The geographical boundary range shp data of the study area were obtained. Meteorological observation stations in the study area provided numerical observation results according to extreme weather research indicators. At the same time, the China Southern Power Grid Company provided the location information, the number of faults and the corresponding fault voltage of each fault area in the study area.

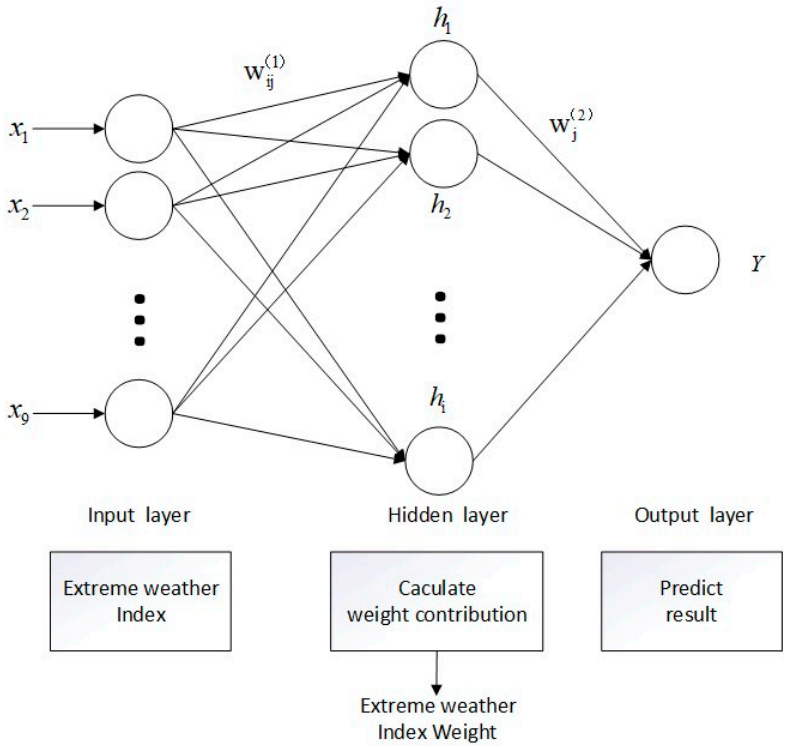

Figure 2. GA-BP neural network model diagram.

The converted extreme weather indicator data and circuit failure data were spatially correlated and matched, and ArcMap geographic information processing software was used for processing to ensure that the fault data in each study area were matched with the corresponding meteorological data.

The structure of the neural network model for correlation analysis between extreme weather and circuit faults based on the GA-BP algorithm is defined as follows:

To realize construction of the sample set, pre-classification is performed based on the extreme weather index data and circuit fault data. The sample set is divided into training set, verification set and test set to ensure the generalization ability and stability of the model. The definition of extreme weather is mainly based on the pre-classification of indicator data and the data of the fault area, including the number of faults.

The input layer contains nine nodes corresponding to the nine extreme weather indicators: CDD, CWD, total annual precipitation, SDII, R25 mm, R50 mm, R95p, HTD, and FD.

The output layer contains 1 node which is the count of circuit faults divided by different voltages.

The genetic algorithm is responsible for macroscopic search of optimal hyperparameters. The gradient descent of the multi-layer perceptron (MLP) is responsible for micro-adjusting the network weight.

Genetic algorithms are used to optimize neural network parameters (number of hidden layer nodes, regularization parameters, and learning rate) by simulating natural selection (selection, crossover, variation, etc.) to find the best combination of parameters in the search space to minimize the objective function (MSE). The multi-layer perceptron (MLP) uses gradient descent to optimize the weight of the neural network.

The steps for optimizing the initial weight based on the GA-BP algorithm generally include the following: chromosome coding, population initialization, adjustment, fitness function, selection, crossover, variation, and iteration, etc.

The parameters of the neural network model are set as follows: the genetic algorithm sets 1 hidden layer; the number of nodes in the hidden layer has the range [5, 100]; the regularization parameter alpha has the range [0.0001, 0.1]; the initial learning rate has the range [0.0001, 0.1]; and the number of iterations of the genetic algorithm is set to 1000 times. We set the maximum number of iterations of the multi-layer perceptron (MLP) neural network during training to 500, using the non-linear activation function ReLU.

Dropout layers were initially tested but removed due to limited improvement in validation loss, suggesting that the dataset size and regularization parameters were sufficient to prevent overfitting.

The loss function uses the mean square error (MSE) as the loss function, and obtains the lowest MSE by iterating 1000 times, determining the optimal solution of the best number of hidden layer nodes, regularization parameters and learning rate.

In the training process, the initial weight and bias after GA optimization are used as the initial state of the BP neural network. We implement the backpropagation algorithm to further minimize error by adjusting the weight and bias. We use Adam to update the weights. In order to prevent overfitting, the loss of the validation set is monitored, and the training is stopped in advance when the loss no longer decreases.

The dataset is divided into a training set, a validation set, and a test set (80% training, 20% testing).

The model performance is evaluated on the test set using the R^2 (coefficient of determination) and MAE (average absolute error) indicators to evaluate the model's effect.

The importance evaluation of the global weight associated with extreme weather and circuit faults based on the GA-BP neural network is calculated as follows:

After the training is completed, the contribution of each input feature to the output (count of failures) is calculated, and the importance of each weather indicator is assessed by analyzing the post-training weights.

The contributions of each layer are aggregated, quantifying the relative importance of each input feature.

$$u_i = f(X) \tag{2}$$

$$\mathrm{h_j} = f\left(\sum_{i=1}^{9} w_{ij}^{(1)} \cdot a_i + b_j^{(1)}\right) \tag{3}$$

$$Z = f\left(\sum_{j=1}^{7} w_j^{(2)} \cdot h_j + b^{(2)}\right) \tag{4}$$

We assume that the 9 nodes in the input layer are X = [x1, x2, x3. . ., x9], and the hidden layer, they are H = [h1, h2, h3. . ., hi]. The weight matrix from the input layer to hidden layer is $W^{(1)}$, where $w_{\mathrm{ij}}^{(1)}$ represents the weight from input node h_j to hidden layer node.

$f(\cdot)$ is the activation function, and $b_j^{(1)}$ is the bias of the hidden layer node h_j. The output layer node is Z, and the weight matrix from the hidden layer to the output layer is $W^{(2)}$, where $w_j^{(2)}$ represents the weight from the hidden layer node to the output layer node Z. $b^{(2)}$ indicates the offset of the output layer node.

Specifically, the contribution of each input feature to the output can be calculated using the following steps.

$$C_j = w_j^{(2)} \cdot h_j \tag{5}$$

C_j is the contribution of hidden node h_j to the output.

$$C_{ij} = w_{ij}^{(1)} \cdot x_i \tag{6}$$

C_{ij} is the contribution of input feature a_i to hidden node h_j.

$$C_i = \sum_{j=1}^{7} C_{ij} \cdot w_j{}^{(2)} \tag{7}$$

C_i is the total contribution of the input feature a_i to the output Z.

To compare the contributions of individual input features, we can normalize each C_i so that all C_i sum to 1:

$$u_i = \frac{C_i}{\sum_{i=1}^{9} C_i} \tag{8}$$

The closer μ is to 0, the less risky the event is, and the closer μ is to 1, the more risky the event is. Using this function as a method to calculate the confidence can effectively express the confidence of these kinds of factors.

Through the above steps, the relative importance of each weather index to transmission line faults can be quantified, and the global weight of each input feature can be reflected, which can provide a basis for further decision analysis.

3. Results

3.1. Model Evaluation Result

In this study, meteorological data of 376 meteorological observation stations in five provinces of the China Southern Power Grid (Guangdong, Guangxi, Yunnan, Guizhou and Hainan) and fault records of different voltage transmission lines (10 kv, 35 kv, 110 kv, 220 kv and 550 kv) were used to conduct experiments, and the experimental results were analyzed. The experimental results show that the model has high precision and can fully display the fault risk levels of a large range of transmission lines in five provinces of the China Southern Power Grid.

The loss function curves of 15 rounds of model training show that most of the models converge within 300 times, and the high-voltage data with relatively few training data converge within 800 times.

In this experiment, MAE was used to measure the prediction error.

The Figure 3 line chart specifically shows the test set prediction and fitting effect based on the GA-BP model.

According to the GA-BP model prediction test results, the model can better predict and distinguish the number of high and low risks and generally reveals the large area of high risk and transmission line faults that easily occur.

As can be seen from the MAE results in Figure 4, the absolute mean error shows a decreasing trend as the voltage increases. Combined with the statistical data, it can be seen that the number of incidents usually occurring in high-voltage transmission lines is relatively small, and the average count of failures in high-frequency areas from low voltage to high voltage is roughly 4000, 350, 150, 100 and 30 per year. Under the same voltage, the MAE gap between three years is small, and the number of transmission circuit failures on the side surface in each year is average, indicating that the prediction error is low and the model has excellent performance.

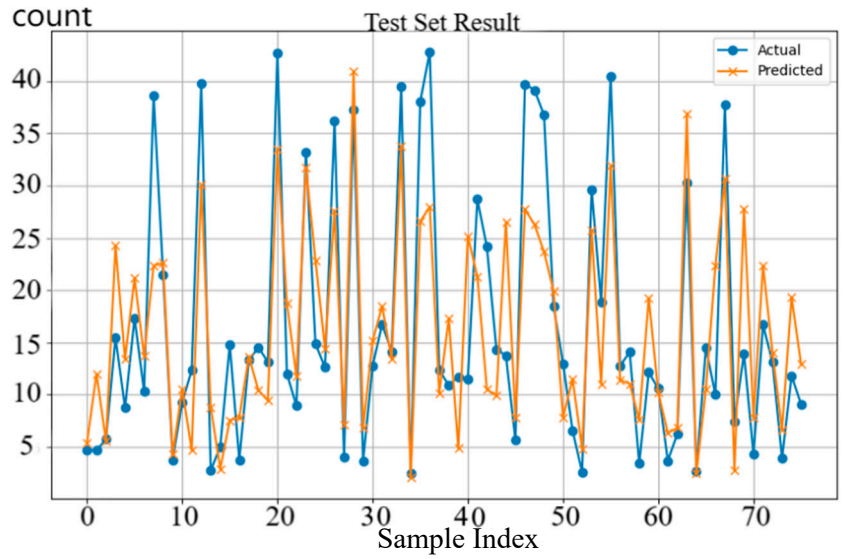

Figure 3. Model prediction test results.

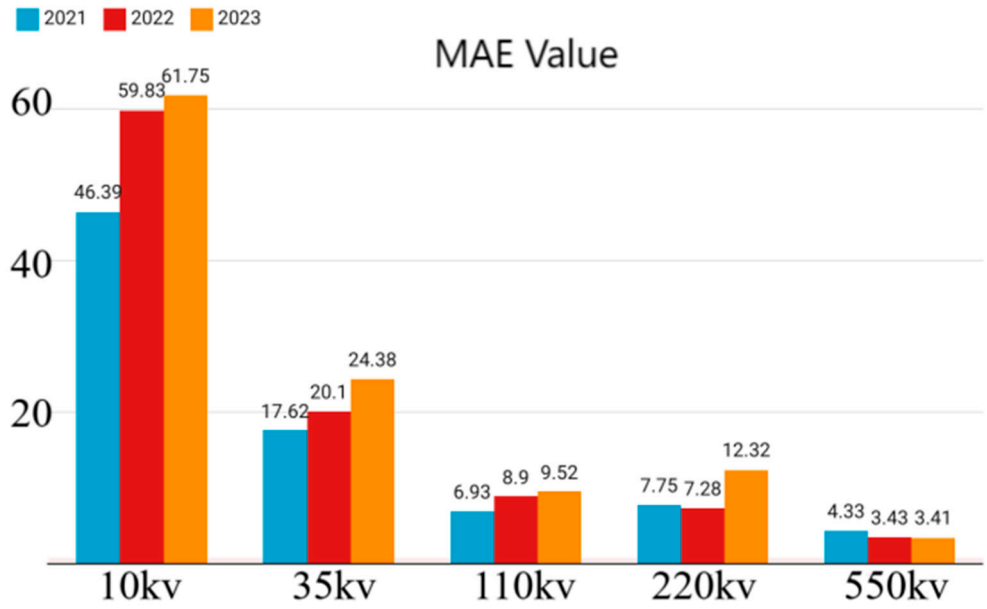

Figure 4. MAE results at different voltages.

The slight annual increase in MAE (2021–2023) may reflect evolving climate patterns or grid infrastructure upgrades not fully captured in training data. Future models will integrate dynamic climate projections to enhance temporal adaptability.

3.2. Global Weight Importance of Extreme Weather Features

In order to reveal the global weight importance of the nine input features, line charts are presented in this section to clearly reflect the influence of each feature on different voltage transmission lines.

Figure 5 shows the influence of different extreme weather characteristics on transmission line faults under 10 kv, 35 kv, 110 kv, 220 kv and 550 kv voltages, respectively. It can be seen that at 10 kv, 35 kv, 110 kv and 550 kv, the SDII index results are relatively consistent and occupy a relatively high proportion, while the FD and CDD indices have greater explanatory ability for high-voltage transmission line faults. In the global weight distribution of extreme weather characteristics, the comprehensive ratio of annual precipitation intensity (SDII), maximum continuous dry days (CDD) and frost days (FD) is larger,

indicating that SDII, CDD and FD have better explanatory ability for transmission line faults. This shows that transmission line faults are more likely to occur in areas with high precipitation intensity, long-term drought and long-term low temperature below 0 °C. It also indicates that the region conforming to these characteristics should be the high-risk region of transmission line tripping faults.

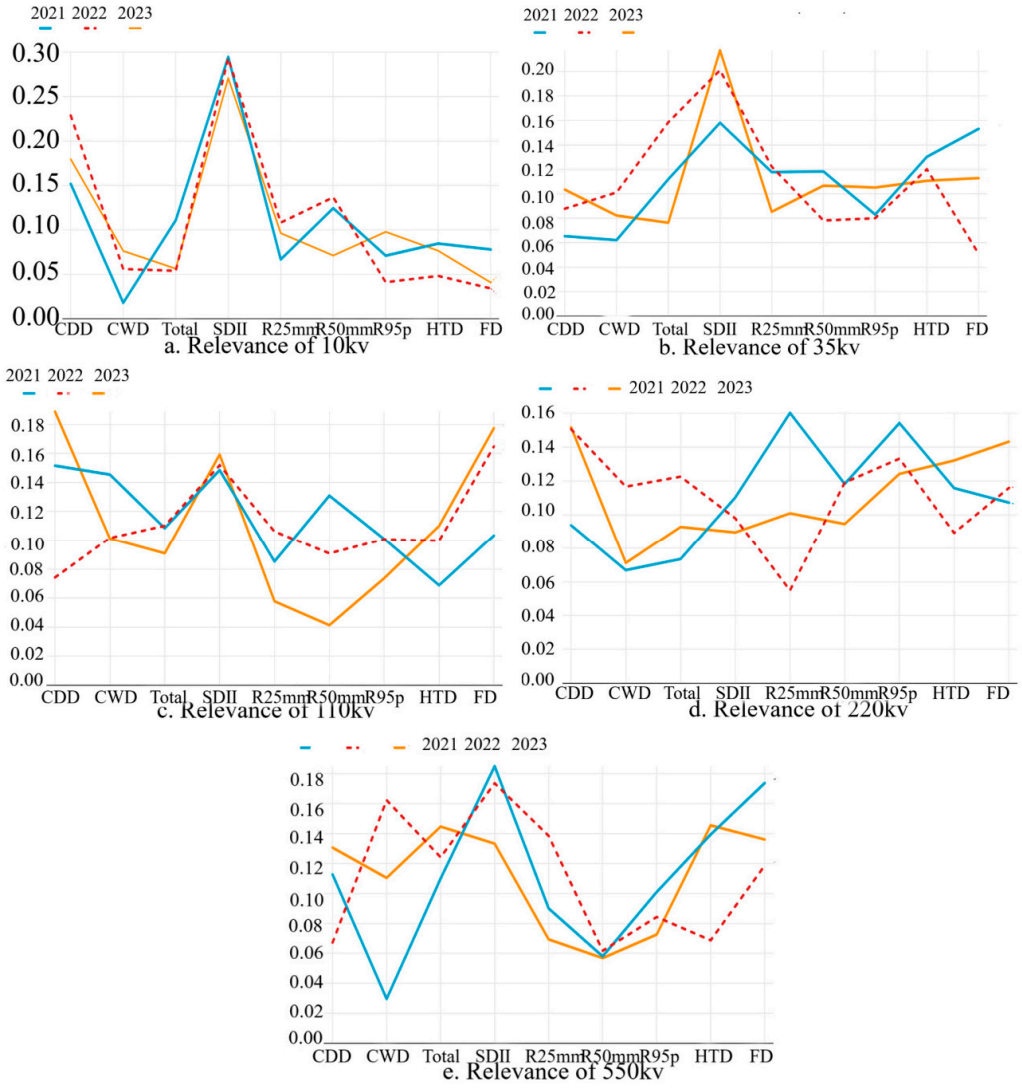

Figure 5. Global weight importance of extreme weather features.

3.3. Fault Risk Levels of Regional Transmission Lines in China Southern Power Grid

Risk levels were categorized based on composite indices rather than direct fault counts. The comparison validates that higher risk indices align spatially with actual fault hotspots. Figure 6 below shows the spatial distribution of the number of actual circuit faults under different voltages in the China Southern Power Grid in 2022.

The effectiveness and accuracy of the GA-BP method can be verified by comparing the number of actual circuit faults with the risk levels obtained by experiments. Figure 7 specifically shows the spatial distribution of regional circuit fault risk levels of the China Southern Power Grid based on the GA-BP neural network method. Compared with the actual number of faults in Figure 6, it can be seen that the spatial distribution rules of the two are highly consistent, which proves that this research method has high accuracy and effectiveness. For example, in the 10 kv distribution, the places with the most circuit failure times are located in the northwest of Guizhou and the south of Yunnan. The high-occurrence area for 35 kv faults is in the north of Guizhou. The high incidence of 110 kv

faults is located in Guizhou and Yunnan provinces. The 220 kv fault high-incidence area is located in Nanning. The 550 kv faults show the same increasing pattern from west to east, and Guangdong Province is the riskier area.

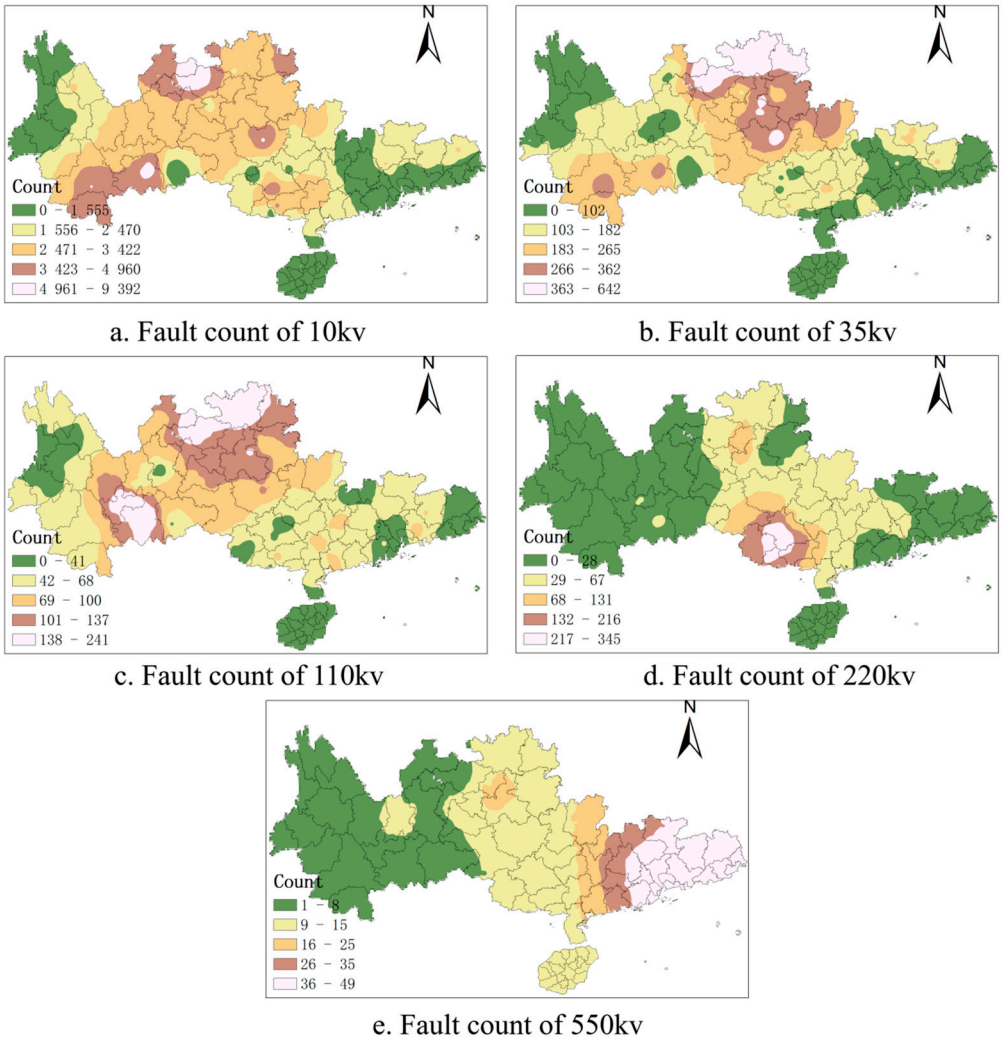

Figure 6. Spatial distribution of the actual number of circuit faults at different voltages in 2022.

Figure 7 shows the spatial distribution of fault levels of regional circuits in the China Southern Power Grid. In this experiment, the thematic map of fault risk levels for the China Southern Power Grid was successfully constructed.

The following conclusions can be drawn from the analysis:

The medium- and high-risk areas are predominantly located in regions characterized by complex geographical and meteorological conditions and frequent extreme weather events. Notably, these include mountainous areas in Guizhou with rugged terrain, tropical regions in Yunnan with hot climates and heavy rainfall, and coastal areas significantly influenced by marine monsoons.

The experimental results indicate that extreme weather features such as the standardized drought index (SDII), consecutive dry days (CDD), R25 mm, and R50 mm, which were input into the model, provide a robust explanation for transmission line faults.

Under relatively lower voltage conditions, specifically, 10 kV, 35 kV, and 110 kV, the risk of transmission line faults exhibits a discernible pattern. For instance, cities such as Yuxi, Puer, Mengzi, Bijie, Zunyi, Hechi, and Duyun consistently exhibit medium- and high-risk levels.

Under 220 kv and 550 kv high voltage conditions, the number of transmission line faults is relatively small, but it also shows that the risk level in border coastal areas is greater than that in inland areas; in particular, the 220 kv transmission line in Nanning area has the highest risk. The results for the 550 kv risk level show that Guangdong Province's risk level is the highest among the provinces, showing a rising trend from west to east. Combined with the global weight importance of extreme weather features, it can be inferred that the important cause of high voltage transmission line fault comes from high-intensity-rainfall-related factors.

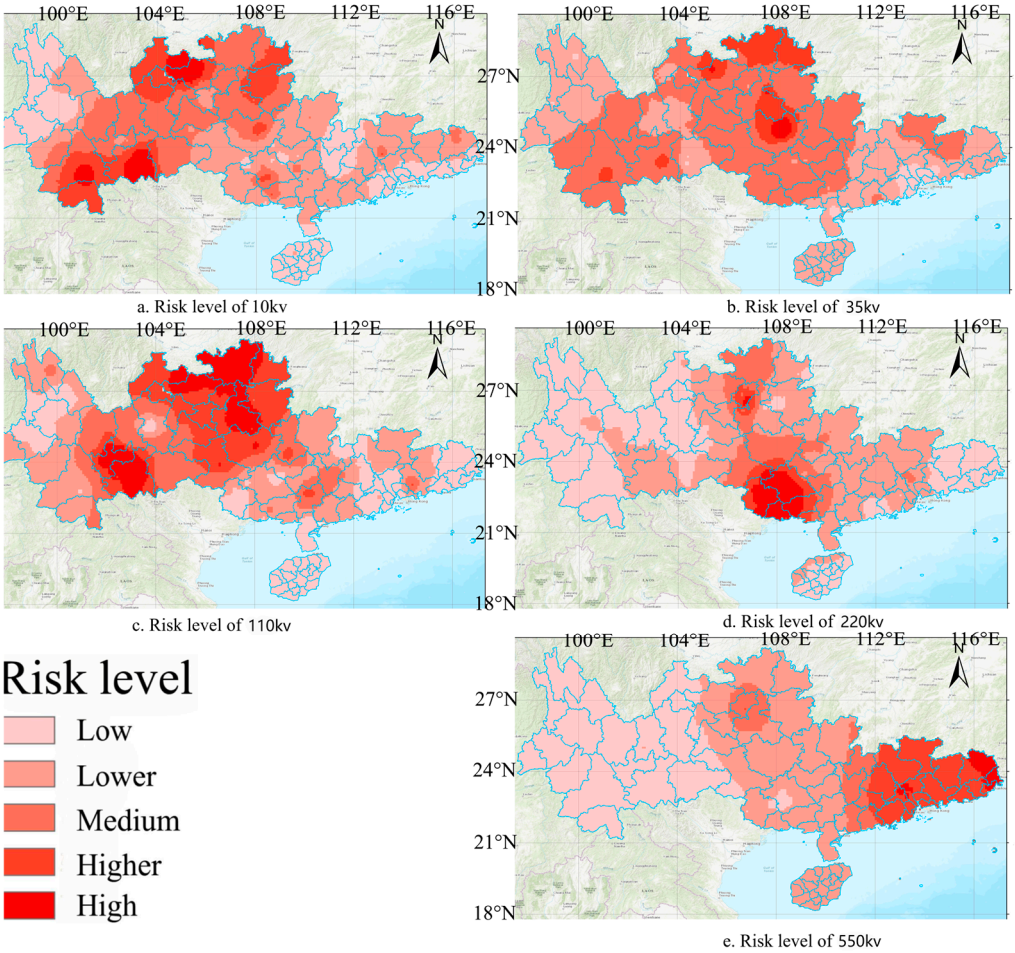

Figure 7. Spatial distribution of the actual number of circuit faults at different voltages.

4. Conclusions

To address the issue of inadequate risk assessment for transmission circuit failures caused by extreme weather in the China Southern Power Grid, this paper proposes a BP neural network model optimized by genetic algorithms. This model evaluates the operational risks of power grids under extreme weather conditions across five provinces within the China Southern Power Grid. A network model incorporating the characteristics of extreme weather and circuit fault inputs has been developed, introducing a novel approach to assess the risk of extreme weather indicators using the global weight evaluation method of neural networks. The experimental results yielded the global weight influence values for various types of extreme weather, evaluated the model's performance, and effectively identified high-risk areas for large-scale transmission circuit failures in the China Southern Power Grid.

Compared to conventional statistical models, the GA-BP neural network captures complex nonlinear interactions between meteorological factors and fault risks, achieving

higher accuracy in spatially heterogeneous regions. This highlights the potential of machine learning in dynamic risk assessment under climate change [27].

The findings demonstrate that this method offers significant advantages in terms of accuracy and stability, providing a reliable foundation for power grid operation risk management and is applicable to multivariate forecasting research in other domains.

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