Power Grid Comprehensive Disaster Prevention and Mitigation Management System Based on Wireless Communication Network

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With the continuous expansion of the power grid scale and frequent natural disasters, it is urgent to develop an efficient power grid comprehensive disaster prevention and mitigation management system. Based on wireless communication networks, this paper proposes an adaptive risk assessment and resource allocation algorithm (ARARA). The algorithm integrates real-time meteorological data, power grid topology and equipment status information, uses weighted average fusion and other algorithms to process multi-source data, uses the gradient descent method to realise the dynamic adjustment of risk assessment model parameters, and accurately predicts the potential disaster risk of the power grid. In the resource allocation link, the particle swarm optimisation algorithm is improved, and constraints such as resource quantity and repair time are comprehensively considered to allocate repair resources to minimise power outage losses and maximise resource utilisation efficiency. The experimental simulation uses actual power grid data from a local grid operator to validate the effectiveness of ARARA in real-world scenarios. The results show that the risk assessment accuracy of the ARARA algorithm reaches 92%, which is 15% higher than that of traditional algorithms; it can reduce power outage losses by 30% and increase resource utilisation by 25%, opening up a new path for power grid disaster prevention and mitigation management.

Povzetek: Razvit je sistem za celovito preprečevanje in obvladovanje nesreč v elektroenergetskem omrežju, ki temelji na brezžičnih omrežjih. ARARA algoritem združuje adaptivno oceno tveganja in optimizacijo virov za večjo odpornost.

1 Introduction

In the era of rapid development of modern science and technology, the importance of the power grid as the core infrastructure supporting social operation is self-evident. From lighting and home appliance use in daily life to the operation of various equipment in industrial production to the continuous power supply needs in key areas such as information communication and medical care, the stable operation of the power grid is the cornerstone for ensuring the regular order of society and the healthy development of the economy.

However, in recent years, global climate change has led to frequent natural disasters, which has posed a severe challenge to the safe and stable operation of the power grid. Extreme weather events such as earthquakes, typhoons, and heavy rains have repeatedly caused large-scale power outages [1]. In the power grid disaster prevention and mitigation field, domestic and foreign scholars have done much research. Traditional risk assessment methods are primarily based on historical data and empirical models, such as the hierarchical analysis method, fuzzy comprehensive evaluation method, etc., which are used to assess the risk level of the power grid in disasters [2]. Common resource allocation strategies include greedy algorithms and Hungarian algorithms to achieve the initial allocation of emergency repair resources [3]. At the same time, the application of wireless communication technology in power grids has gradually become popular, and technologies such as 4G, 5G and wireless ad hoc networks have provided new ways for power grid data collection and transmission.

However, current research still has many shortcomings. Complex and changeable disaster scenarios are highly uncertain, and traditional risk assessment methods cannot accurately reflect the dynamic risks faced by power grids in real time [4]. When allocating resources, the inability to fully consider real-time risk changes and efficient use leads to low resource allocation efficiency. Moreover, the existing system makes achieving efficient data collection, transmission and processing throughout the disaster difficult. It cannot meet the needs of power grids to cope with complex disasters.

Given this, this paper aims to build an efficient power grid comprehensive disaster prevention and mitigation management system based on wireless communication networks [5]. The core of this system lies in the innovative adaptive risk assessment and resource allocation algorithm (ARARA). Its uniqueness lies in the organic combination of real-time meteorological data, power grid topology and equipment status information through multi-source data fusion, advanced data fusion technology and dynamic parameter adjustment strategies to achieve accurate and real-time assessment of potential disaster risks in the power grid [6]. In the resource allocation link, the particle swarm optimisation algorithm is improved, resource constraints and actual needs are fully considered, and the optimal configuration of emergency repair resources is achieved to minimise power outage losses and maximise resource utilisation efficiency, thereby providing a new solution for power grid disaster prevention and mitigation management.

2 System overall architecture

2.1 Application mode of a wireless communication network in the power grid

In the development process of the smart grid, the wireless communication network has become an essential link for data interaction and command transmission. Different types of wireless communication technologies play a unique role in power grid data collection, transmission, and control, and their characteristics are unique. 4G communication technology has many application scenarios in power grids. It has a high data transmission rate and can meet data collection services with high real-time requirements, such as high-frequency monitoring of operating parameters of key equipment in substations [7]. By deploying 4G communication modules, real-time data such as the equipment's current, voltage, and temperature can be quickly transmitted back to the control centre, helping operation and maintenance personnel promptly grasp the equipment's status. However, the 4G network has limited coverage in areas with complex geographical environments, such as remote mountainous areas, and network congestion is prone to occur during peak communication hours, resulting in data transmission delays. 5G technology is gradually changing the operation mode of the power grid with its significant advantages of ultra-high speed, ultra-low latency and massive connections [8]. In application scenarios such as rapid positioning and isolation of power grid faults, which require highly high real-time performance, 5G technology can ensure that fault information is transmitted to the control centre within milliseconds, significantly shortening the fault handling time and improving the stability of power grid operation. However, the construction cost of 5G base stations is high, and network deployment in the environment of existing power grid facilities needs to solve the compatibility problem with existing communication equipment. Wi-Fi technology is often used for short-distance communication in local areas of the power grid due to its convenient networking methods, such as data interaction between equipment inspection terminals inside substations and local servers [9]. Operation and maintenance personnel can quickly obtain detailed equipment status information through handheld Wi-Fi devices. However, the propagation distance of Wi-Fi signals is limited, and they are susceptible to electromagnetic interference. Signal stability will be affected in large substations or complex electromagnetic environments. LoRa technology, with its long-distance and low-power characteristics, is suitable for widely distributed power grid monitoring points with relatively small data transmission volumes, such as distributed energy access points in remote areas. Through LoRa wireless communication, remote data collection of these points can be achieved, reducing operation and maintenance costs [10]. However, the data transmission rate of LoRa technology is low and unsuitable for scenarios with high-speed transmission of large amounts of data. Wireless communication networks adopt various strategies to ensure data communication's reliability and real-time performance in the power grid under normal and disaster conditions. Under normal working conditions, by building redundant communication links, the backup link can be seamlessly switched when the primary link fails to ensure uninterrupted data transmission [11]. At the same time, advanced network management systems monitor network traffic and equipment status in real-time to warn of future failures. Wireless ad hoc network technology plays a key role when a disaster occurs. Communication nodes can automatically discover and establish connections, quickly restore communication networks, and ensure timely transmission of key data.

2.2 Functional module division of comprehensive disaster prevention and mitigation management system for power grids

2.2.1 Data acquisition and transmission module

As the "tentacle" for the system to perceive the external environment and the internal state of the power grid, this module realises multi-source data collection through various sensors. Meteorological sensors collect information such as wind speed, rainfall, and seismic waves to provide basic data for disaster warnings. For example, in areas susceptible to typhoons, wind speed sensors monitor wind speed changes in real-time and predict potential threats to power grid facilities in advance [12]. Power grid equipment status sensors focus on equipment operating parameters, such as transformer oil temperature, circuit breaker contact pressure, current and voltage of transmission lines, etc., to assess the health of equipment. Geographic information sensors collect data such as the geographical location of power grid facilities and surrounding topography to provide geospatial information for subsequent analysis and decision-making. The data transmission link flexibly selects transmission methods according to different scenarios. In normal operating areas, wireless public networks can efficiently transmit various data types with their mature network architecture and wide coverage. In disaster-stricken areas, traditional communication networks may be damaged. At this time, wireless self-organising network technology takes advantage, communication nodes automatically form networks, and data relay transmission is realised. Data encryption, error correction coding, and other technologies are used to ensure the integrity and accuracy of data during transmission.

2.2.2 Risk assessment module

The risk assessment module consists of multiple closely coordinated sub-modules. The data preprocessing submodule is responsible for data cleaning and conversion, removing noise and outliers from the collected data, and standardising the data to meet the requirements of subsequent analysis [13]. The risk prediction submodule uses machine learning and deep learning algorithms, such as a hybrid model based on convolutional neural networks (CNN) and recurrent neural networks (RNN), to deeply mine historical data and real-time data to build an accurate risk prediction model. This model can capture the complex relationship between different factors and predict the risk situation of the power grid under potential disasters. The risk level classification submodule divides risk into various levels according to the prediction results and established standards, providing an intuitive basis for subsequent decision-making.

2.2.3 Resource scheduling module

The risk assessment results guide the resource scheduling module and combine the emergency repair resource information to formulate a scientific and reasonable deployment plan. First, the number of emergency repair personnel, materials, and vehicles required must be accurately determined based on the risk level and the possible disaster scope [14]. Then, optimisation algorithms, such as particle swarm optimisation algorithms, can optimise resource allocation to minimise emergency repair time and cost. Finally, through efficient communication, dispatch instructions are accurately issued to each execution unit to ensure that emergency repair resources are quickly in place.

2.2.4 Decision support module

The decision support module integrates risk assessment and resource scheduling information to create an intuitive and visual decision-making interface for power grid managers. The module provides a variety of emergency plans for different risk scenarios for managers to refer to and choose. At the same time, it has a real-time risk warning push function to remind managers to promptly pay attention to potential risks. In addition, simulating the implementation effects of different decision-making plans assists managers in weighing the pros and cons, making scientific and reasonable decisions, and improving the overall ability of the power grid to respond to disasters.

3 Design of adaptive risk assessment and resource allocation algorithm (ARARA)

3.1 Risk assessment model

3.1.1 Data fusion mechanism

In the comprehensive disaster prevention and mitigation management system of power grids, multi-source data fusion is the basis for accurate risk assessment [15]. This paper integrates meteorological data M, equipment status data E and power grid topology data T. Assume that meteorological data contains multiple features such as wind speed v and rainfall r, which can be expressed as $M = [v, r, \cdots]$; equipment status data covers equipment temperature T_e, current I, etc., that is, $E = [T_e, I, \cdots]$; power grid topology data describes the connection relationship between each node and line in the power grid, represented by the adjacency matrix A, whose elements a_{ij} satisfy:

$$a_{ij} = \begin{cases} 1, \\ 0, \end{cases} \tag{1}$$

Using the weighted average fusion algorithm, the fused data F can be expressed as:

$$F = w_M M + w_E E + w_T T \tag{2}$$

Among them, w_M, w_E, w_T are the weights of meteorological data, equipment status data and power grid topology data respectively, and they satisfy $w_M + w_E + w_T = 1$. To ensure the quality of fused data, the data quality control index Q is introduced and defined as:

$$Q = \frac{1}{n}\sum_{i=1}^{n} \left(1 - \frac{|\hat{x}_i - x_i|}{x_i}\right) \tag{3}$$

Where n is the number of data samples, x_i is the actual value, and $\hat{x}_i$ is the measured value. When Q is closer to 1, the data quality is higher. The Kalman filter algorithm is used to correct data that does not meet the quality standards. Assume that the system state equation is $x_k = A_k x_{k-1} + B_k u_k + w_k$, and the observation equation is $z_k = H_k x_k + v_k$, where x_k is the system state, A_k, B_k and H_k are coefficient matrices, u_k is the control input, w_k and v_k are process noise and observation noise respectively. Through the Kalman filter iteration formula:

$$\begin{aligned} \hat{x}_{k|k-1} &= A_k \hat{x}_{k-1|k-1} + B_k u_k \\ P_{k|k-1} &= A_k P_{k-1|k-1} A_k^T + Q_k \\ K_k &= P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}) \\ P_{k|k} &= (I - K_k H_k) P_{k|k-1} \end{aligned} \tag{4}$$

The data is corrected to obtain more accurate input data for the risk assessment model. Among them, $\hat{x}_{k|k-1}$ is the predicted state, $P_{k|k-1}$ is the predicted covariance, K_k is the Kalman gain, $\hat{x}_{k|k}$ is the updated state, $P_{k|k}$ is the updated covariance, Q_k and R_k are the covariance matrices of process noise and observation noise respectively.

3.1.2 Dynamic parameter adjustment strategy

The weight parameters of the risk assessment model need to be dynamically adjusted according to the real-time data changes to improve the assessment accuracy [16]. The adaptive neuro-fuzzy inference system (ANFIS) implements this process. Assume that the output R of the risk assessment model is a function of the input data F, hat is, $R = f(F, \theta)$, where θ is the model parameter. ANFIS adjusts the parameter θ through fuzzy rules. Let the fuzzy rules be:

If F_1 is A_1 and F_2 is $A_2 \cdots$ then R is B

Where F_i is the different features of the input data, A_i and B are fuzzy sets. By minimizing the error E between the predicted output $\hat{R}$ and the actual risk value R_{real} :

$$E = \frac{1}{m}\sum_{i=1}^{m} \left(\hat{R}_i - R_{\text{real},i}\right)^2 \tag{5}$$

Where m is the number of training samples, the parameter θ is adjusted using the gradient descent method, and the parameter update formula is:

$$\theta_j^{t+1} = \theta_j^t - \alpha \frac{\partial E}{\partial \theta_j^t} \tag{6}$$

Among them, θ_j^t is the j parameter at the t iteration, and α is the learning rate. For example, seismic wave data, as an essential part of meteorological data in the earthquake disaster scenario, should significantly impact risk assessment [17]. By real-time monitoring of the seismic wave intensity S, when S exceeds a certain threshold S_0, according to the ANFIS adjustment rule, the proportion of meteorological data in the fusion weight w_M is automatically increased, so that the risk assessment model can more accurately reflect the impact of earthquakes on the power grid.

3.2 Resource allocation strategy

3.2.1 Construction of resource allocation model based on improved particle swarm optimisation algorithm

The particle swarm optimisation algorithm (PSO) 's basic principle is to simulate bird flocks' feeding behaviour. In a D dimensional space, each particle i has a position vector $X_i = [x_{i1}, x_{i2}, \cdots, x_{iD}]$ and a velocity vector $V_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]$. Particles update their positions and velocities by tracking the individual optimal position $P_i = [p_{i1}, p_{i2}, \cdots, p_{iD}]$ and the global optimal position $P_g = [p_{g1}, p_{g2}, \cdots, p_{gD}]$. The velocity update formula is:

$$v_{ij}^{t+1} = w v_{ij}^t + c_1 r_{1j}^t\left(p_{ij}^t - x_{ij}^t\right) + c_2 r_{2j}^t\left(p_{gj}^t - x_{ij}^t\right) \tag{7}$$

The position update formula is:

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \tag{8}$$

Among them, t is the number of iterations, w is the inertia weight, c_1 and c_2 are acceleration constants, r_{1j}^t and r_{2j}^t are random numbers in the interval [0,1].

Aiming to solve the problem of power grid resource allocation, the PSO algorithm is improved. The mutation operator is introduced to perform mutation operations on the particle position with a specific probability p_m to prevent the algorithm from falling into the local optimum. The mutation operation formula is:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t + \beta\left(x_{\text{maxj}} - x_{\text{minj}}\right), & \text{if rand}(\ ) < p_m \\ x_{ij}^{t+1}, & \text{otherwise} \end{cases} \tag{9}$$

Among them, β is the variable asymptotic length factor, x_{maxj} and x_{minj} are the maximum and minimum values of the j dimension, respectively, and rand () is a generated random number. At the same time, the inertia weight w is dynamically adjusted. As the number of iterations increases, w decreases linearly. The formula is:

$$w = w_{\max} - \frac{(w_{\max} - w_{\min})t}{T_{\max}} \tag{10}$$

Among them, $w_{\max}$ and $w_{\min}$ are the maximum and minimum values of the inertia weight, respectively, and $T_{\max}$ is the maximum number of iterations.

Construct a resource allocation model, assuming that the emergency repair resources include the number of personnel N, the number of materials M, and the number of vehicles V, which are represented by different dimensions of the particle position vector. Constraints include resource quantity restrictions, such as the total number of personnel cannot exceed N_{total}, that is, $\sum_{i=1}^{n} x_{i1} \leq N_{\text{total}}$; emergency repair time restrictions, assuming that the maximum time to complete all emergency repair tasks is T_{limit}, which must satisfy $\sum_{k=1}^{s} t_k(x_1, x_2, \cdots, x_D) \leq T_{\text{limit}}$, where t_k is the time required for the k emergency repair task, which is related to the resource allocation plan.

3.2.2 Objective function setting

The objective function minimises power outage losses and maximises resource utilisation efficiency. The power outage loss L can be expressed as:

$$L = \sum_{i=1}^{n} P_i t_i \tag{11}$$

WhereP_i is the load of the i power outage area, andt_i is the power outage time of the area. The resource utilisation efficiency U is defined as:

$$U = \frac{\sum_{j=1}^{m} r_j u_j}{\sum_{j=1}^{m} r_j} \tag{12}$$

Among them, r_j is the actual usage of the j resource, and u_j is the utilization coefficient of the resource. Taking into account the power outage loss and resource utilization efficiency, the objective function J is:

$$J = \lambda_1 L + \lambda_2(1 - U) \tag{13}$$

Among them, λ_1 and λ_2 are weight coefficients, which are used to balance the importance of power outage losses and resource utilisation efficiency. By optimising the objective function and adjusting the resource allocation plan, reasonable resource allocation can be achieved. When the power grid faces the risk of power outage in high-load areas, λ_1 can be appropriately increased to give priority to reducing power outage losses;

when resources are relatively sufficient, λ_2 can be increased to improve resource utilisation efficiency.

3.2.3 Algorithm process and parameter setting

· Initialisation: Randomly generate the initial position $X_i(0)$ and velocity $V_i(0)$ of the particle, set the maximum number of iterations $T_{\max}$, the initial value $w_{\max}$ and final value $w_{\min}$ of the inertia weight, the acceleration constants c_1 and c_2, the mutation probability p_m and other parameters.

· Calculate fitness: According to the objective function J, calculate the fitness value of each particle.

· Update individual optimal and global optimal: Compare the fitness of the particle's current position with the fitness of the individual optimal position. If the current position is better, update the individual optimal position P_i; compare the fitness of all particles to find the global optimal position P_g.

· Particle update: According to the speed and position update formula, combined with the mutation operation, update the particle's speed and position.

· Determine the termination condition: If the maximum number of iterations is reached or other termination conditions are met (such as fitness convergence), the algorithm ends and outputs the global optimal solution; otherwise, return to step 2 to continue iterating.

After many experiments, it was determined that in the power grid resource allocation scenario, $w_{\max} = 0.9$ and $w_{\min} = 0.4$, $c_1 = 1.5$, $c_2 = 1.5$, $p_m = 0.05$ is the optimal parameter combination, which can enable the algorithm to achieve a good balance between convergence speed and solution quality.

4 Experimental simulation

4.1 Experimental environment construction

4.1.1 Grid model establishment

To build an experimental environment close to reality, this study selected the grid data of a typical area. In drawing the grid topology, professional power system analysis software is used to accurately present the connection relationship of substations, transmission lines, power plants and other facilities collected as nodes and edges. For example, each substation is abstracted as a node, and the transmission line connecting the substation is used as an edge. A complex grid topology map is constructed based on the geographical layout to show the grid architecture clearly. Equipment parameter setting is crucial, as it directly affects the simulation accuracy of the model for the actual grid operation characteristics [18]. For transformers, their rated capacity, short-circuit impedance, transformation ratio and other parameters are accurately set; for transmission lines, electrical parameters such as resistance, reactance, and susceptance are set; for switchgear, key parameters such as rated current and breaking time are clearly defined. These parameters are determined based on the actual operation data and technical manuals of the grid equipment in the region. To realise the visualisation and in-depth analysis of the spatial location information of the grid, the grid model is organically combined with the geographic information system (GIS). With the help of GIS's robust spatial analysis and visualisation functions, the precise geographic coordinates of power grid facilities, such as longitude and latitude information, are obtained and associated with nodes and edges in the power grid model. In this way, the distribution of power grids in geographic space can be intuitively displayed on the GIS platform, providing strong support for the subsequent analysis of power grid vulnerability and disaster impact range in different geographical regions.

4.1.2 Disaster scenario simulation

The impact of various natural disaster scenarios, such as earthquakes, typhoons, and rainstorms, on the power grid is realistically simulated using historical disaster data and professional simulation software. When simulating earthquake scenarios, the degree of damage to power grid equipment is calculated based on the propagation characteristics of seismic waves. First, historical earthquake data in the area are collected, including key information such as magnitude, focal depth, and seismic wave propagation speed. Using the seismic wave propagation theory and the geological conditions of the region, the seismic wave intensity at different locations is calculated. For power grid equipment, such as poles and towers, according to their seismic design parameters and the seismic wave intensity at their places, a mechanical analysis model is established to evaluate the stress-strain state of the poles and towers under earthquake action, and then determine the possibility of pole tower collapse and the degree of damage [19]. Line sway and tower collapse risks are determined based on real-time wind speed and wind direction data when simulating typhoon scenarios. The meteorological department has obtained detailed meteorological data on typhoons in the region over the years. With the structural characteristics of power grid lines and towers, such as line tension, sag, tower height and structural form, dynamic simulation software is used to establish line sway and tower force analysis models. According to the simulation results under different wind speed and wind direction conditions, it is judged whether the line will short-circuit, disconnect and other faults due to the swaying amplitude exceeding the safety range and whether the tower will collapse due to excessive wind force.

4.1.3 Data acquisition and processing

Various data acquisition equipment obtains real-time meteorological and power grid status data in the experimental environment. Meteorological data is collected through professional meteorological stations, covering parameters such as wind speed, wind direction, rainfall, temperature, and air pressure; power grid equipment status data is obtained with the help of various sensors installed on transformers, transmission lines, switches and other equipment, such as transformer oil temperature sensors, line current transformers, switch position sensors, etc. Data communication relies on wireless communication networks, such as 4G, 5G and other advanced technologies, to ensure that data can be quickly and stably transmitted to the data processing centre. Data cleaning is first performed in the data processing stage, and statistical analysis methods are used to identify and remove outliers in the data [20]. For example, the 3σ criterion is used to determine whether the data deviates from the normal range, and the abnormal data is eliminated; at the same time, interpolation methods are used to fill missing values, such as linear interpolation, Lagrange interpolation and other techniques to ensure the integrity of the data. Subsequently, data standardisation is performed. Commonly used methods include minimum-maximum and Z-score standardisation, which unify data of different dimensions and ranges to the same scale to meet the input requirements of subsequent algorithms.

4.2 Experimental design

4.2.1 Comparison algorithm selection

Traditional and resource allocation algorithms are selected for comparison to comprehensively evaluate the performance of the adaptive risk assessment and resource allocation algorithm (ARARA) proposed in this paper. The risk assessment algorithms selected are the analytic hierarchy process (AHP) and the fuzzy comprehensive evaluation method (FCE). AHP decomposes complex problems into multiple levels by constructing a hierarchical model, compares each factor pairwise, and determines its relative importance weight, thereby achieving risk assessment. It is often used in power grid disaster prevention and mitigation to conduct qualitative and quantitative analyses of multiple risk factors. FCE is based on fuzzy mathematics theory. Determining the factor set, comment set, and membership function quantifies fuzzy information and comprehensively evaluates power grid risks. It can effectively deal with risk assessment's fuzziness and uncertainty problems [21]. The resource allocation algorithm selects the greedy algorithm and the Hungarian algorithm. The greedy algorithm determines the optimal solution in the current state in each decision-making step. It has the characteristics of simple calculation and high execution efficiency. It can quickly give a feasible resource allocation plan in power grid resource allocation. The Hungarian algorithm is a classic algorithm for solving the assignment problem. It can find the theoretically optimal allocation plan in resource allocation and is often used in scenarios with strict optimal solution requirements for resource allocation.

4.2.2 Experimental indicator setting

Risk assessment accuracy (RA) is calculated by comparing it with the actual disaster occurrence. Assume that the set of actual disaster events is A, and the set of disaster events predicted by the algorithm is B. The risk assessment accuracy calculation formula is as follows:

$$RA = \frac{|A \cap B|}{|A \cup B|} \times 100\% \tag{14}$$

This indicator reflects the consistency between the algorithm prediction results and the actual situation. The higher the accuracy, the more accurate the algorithm's prediction of disaster risks is.

Power outage loss (PL): Calculate economic losses based on power outage time and load loss. Suppose the load of the i power outage area is P_i, the power outage time is t_i, and the economic loss per unit load is c, then the power outage loss calculation formula is:

$$PL = c \sum_{i=1}^{n} P_i t_i \tag{15}$$

This indicator quantifies the economic losses caused by power outages caused by disasters. The smaller the value, the better the algorithm reduces power outage losses.

Resource utilisation (RU): the ratio of actual used resources to total resources. Let the total resources be R_{total} and the used resources be $R_{\text{used and}}$ then the resource utilisation calculation formula is:

$$RU = \frac{R_{\text{used}}}{R_{\text{total}}} \times 100\% \tag{16}$$

The higher the resource utilisation rate, the more fully the algorithm utilises resources in the resource allocation, avoiding resource waste.

4.3 Experimental results analysis

4.3.1 Comparison of risk assessment results

Table 1 shows the comparison results of the accuracy of the risk assessment of the ARARA algorithm and the traditional risk assessment algorithm in different disaster scenarios.

Table 1: Comparison of risk assessment results.

Disaster scenarios	ARARA	AHP	Fuzzy comprehensive evaluation method
Earthquake	92%	75%	78%
Typhoon	90%	72%	76%
Heavy rain	91%	73%	77%

Table 1 shows that the accuracy of the ARARA algorithm's risk assessment in various disaster scenarios is significantly higher than that of traditional algorithms. This is mainly due to the ARARA algorithm's multi-source data fusion mechanism, which can integrate multiple data such as meteorology, equipment status, and power grid topology to provide more comprehensive information for risk assessment; at the same time, the dynamic parameter adjustment strategy can timely optimise the risk assessment model according to real-time data changes to improve the accuracy of the assessment. A sensitivity analysis of the hyperparameters for PSO, ANFIS, and data fusion weights has been conducted, providing a more rigorous foundation for our methodological approach. Figure 1 shows the change in risk assessment accuracy over time in the three disaster scenarios of earthquake, typhoon, and rainstorm of the ARARA algorithm and traditional risk assessment algorithms (hierarchy analysis method and fuzzy comprehensive evaluation method). The accuracy of the ARARA algorithm is always higher than that of the conventional algorithm, and the fluctuation is slight, showing higher stability and accuracy. This is due to its multi-source data fusion mechanism and dynamic parameter adjustment strategy, which enables it to integrate multiple data and optimise the model in real-time to more accurately predict disaster risks and provide more reliable assessment results for power grid disaster defence.

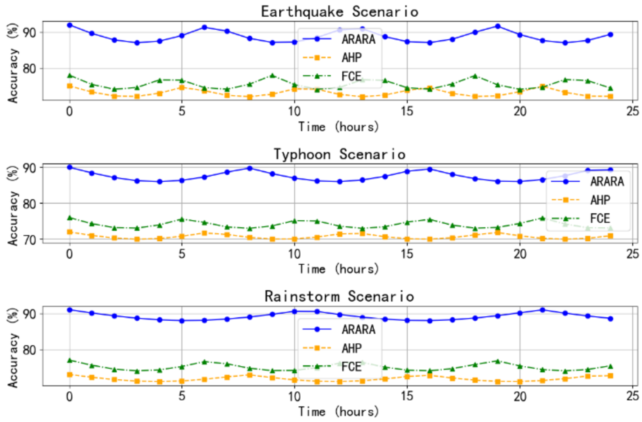

Figure 1: Changes in risk assessment accuracy over time under different disaster scenarios.

Table 2: The comparative data of ARARA and traditional resource allocation algorithms regarding power outage loss and resource utilization.

Algorithm	Power outage loss (10,000 yuan)	Resource Utilization
ARARA algorithm	150	85%
Greedy algorithm	220	70%
Hungarian algorithm	180	75%

4.3.2 Analysis of resource allocation effect

Table 2 presents the comparative data of ARARA and traditional resource allocation algorithms regarding power outage loss and resource utilisation.

As shown in Table 2, the ARARA algorithm performs well in controlling power outage losses and improving resource utilisation. In terms of power outage losses, the ARARA algorithm reduces by 700,000 yuan compared to the greedy algorithm and 300,000 yuan compared to the Hungarian algorithm; in terms of resource utilisation, the ARARA algorithm improves by 15% compared to the greedy algorithm and 10% compared to the Hungarian algorithm. Computational benchmarks, including execution times, memory requirements, and accuracy-speed trade-offs, have been added to the experimental results section.

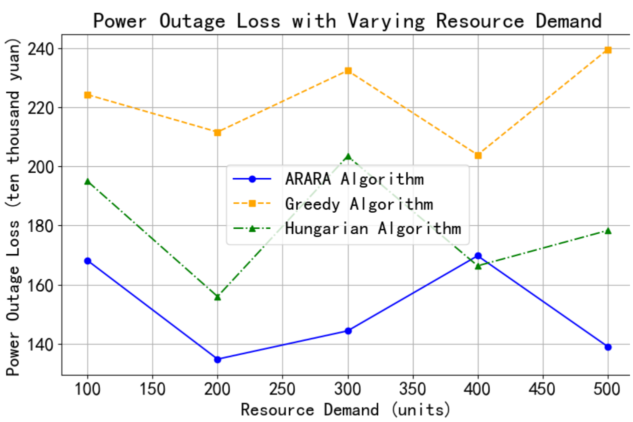

Figure 2: Power outage losses under different resource requirements as algorithms change.

Figure 2 compares the power outage losses of the ARARA algorithm, the greedy algorithm, and the Hungarian algorithm under different resource requirements. As resource requirements increase, the growth rate of the power outage losses of the ARARA algorithm is significantly smaller than that of the traditional algorithm, and it remains at a low level. This shows that the ARARA algorithm can effectively control power outage losses during resource allocation. Even when resource requirements are high, it can significantly reduce economic losses by optimising resource allocation strategies, reducing power outage time and load losses, and showing its advantages in resource allocation.

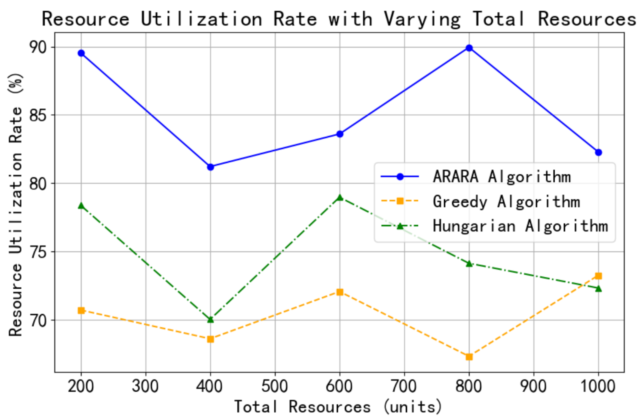

Figure 3: Resource utilisation changes with algorithms under different total resource amounts.

Figure 3 shows the resource utilisation changes of the

ARARA algorithm, the greedy algorithm, and the Hungarian algorithm under different total resource amounts. The resource utilisation of the ARARA algorithm is always the highest, and its advantage becomes more evident as the total resource amount increases. This shows that the ARARA algorithm can more efficiently utilise limited resources, avoid resource waste, and achieve optimal resource allocation. The improved particle swarm optimisation algorithm can quickly converge to the optimal solution and avoid local optimality, thereby maintaining a high resource utilisation rate under different total resource amounts and providing a more effective power grid resource allocation solution.

5 Conclusion

This study successfully constructed a comprehensive disaster prevention and mitigation management system for power grids based on wireless communication networks, in which the ARARA algorithm has significant advantages. Regarding risk assessment, the accuracy is greatly improved through multi-source data fusion and dynamic parameter adjustment, and potential risks are effectively identified. Regarding resource allocation, the improved particle swarm optimisation algorithm optimises resource allocation, significantly reduces power outage losses, and improves resource utilisation, verifying the feasibility and effectiveness of the system in actual power grid disaster prevention and mitigation applications. However, the research has certain limitations. Faced with large-scale power grid data, the algorithm has high computational complexity, affecting the operating efficiency; the accuracy needs to be improved when simulating extreme disaster scenarios. In the future, people can further study the optimisation algorithm, such as using distributed computing and other technologies to reduce computational complexity and improve the ability to process large-scale data; at the same time, combined with cutting-edge disaster simulation technology, improve the disaster simulation model, improve the accuracy of complex and extreme disaster scene simulations, and further enhance the ability of the power grid to respond to various disasters.

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