International Journal of Power and Energy Systems, Vol. 44, No. 10, 2024
An Open Access Paper

ELECTRICAL EQUIPMENT CONDITION MONITORING AND PREDICTIVE MAINTENANCE STRATEGY BASED ON OPTIMISED ANT COLONY ALGORITHM

Jing Li*

Abstract

With the increase of the power system equipment scale and complexity, condition monitoring, and maintenance of electrical equipment become more important. The traditional periodic maintenance strategy has limitations in resource utilisation and maintenance efficiency, which leads to necessary problem exploration. In this paper, a state monitoring and predictive maintenance strategy for electrical equipment based on the optimal ant colony algorithm (OACA) is proposed. The experimental results show that the optimised ant colony algorithm reaches the optimal value of 0.136 after 67 iterations. The efficiency is significantly higher than other methods. According to the optimised detection path, the path length for high failure rate devices is 203 km. The average failure rate devices is 26 km, while the low failure rate devices is 171 km. The total path length is shorter than other algorithms. When the fault increase rate is 20%–50%, the optimised ant colony algorithm achieves better results than the traditional maintenance strategies. In addition, the optimised path reduces the proportion of total cost and significantly improves resource utilisation. In general, this electrical equipment status monitoring and predictive maintenance strategy based on optimised ant colony algorithm can be widely applied in practice, thereby ensuring the safe and stable operation of the power system.

Key Words

Optimised ant colony algorithm, electrical equipment, status monitoring, predictive maintenance, optimisation of inspection path

* College of Mechanical & Electronic Engineering, Shanghai Jianqiao University, Shanghai 201306, China; e-mail: Ljhhh8607@126.com
Corresponding author: Jing Li

(DOI: 10.2316/J.2024.203-0535)

1. Introduction

In today's world, as the artery of modern industry and urban life, the safety and efficiency of the power system are crucial. The health status of electrical equipment directly affects the stability of the whole power system, so the condition monitoring and predictive maintenance of electrical equipment is an important research field in power system management [1]–[3]. However, with the development of intelligent and integrated power network and the increasing complexity of electrical equipment, traditional maintenance strategies, such as cycle-based maintenance and condition-based maintenance have gradually exposed their limitations, including high maintenance cost, low efficiency, and difficulty in adapting to complex system requirements. Therefore, how to efficiently, low-cost, and accurately monitor and maintain electrical equipment is a major challenge in the field of power systems [4]–[6].

According to the needs of modern power grids, intelligent optimisation algorithms have become a promising research direction. Especially, heuristic algorithms, such as ant colony optimisation (ACO) algorithm, show excellent performance in many optimisation problems due to the group cooperation and information sharing. However, the existing ACO algorithm still has many shortcomings when applied in the field of electrical equipment predictive maintenance. For example, convergence speed and optimisation quality can not fully meet the actual needs of complex power networks [7]–[9].

In view of this, in-depth analysis and optimisation of the existing ant colony algorithm to adapt to the actual needs of electrical equipment condition monitoring has become an effective way to improve the reliability of power system. By incorporating advanced monitoring technology into the algorithm and considering the particularity of the electrical equipment operation, such as the interconnection between devices and the adaptability in changing environments, how to improve the convergence speed and quality of algorithms, reduce the complexity and cost of maintaining paths, is the research direction of this article.

On the basis of the existing research, this study introduces a series of innovative points. Firstly, local optimisation is performed on the original ant colony algorithm. The quality and search speed of the algorithm are significantly improved by dynamically adjusting the evaporation and deposition mechanism of pheromones. Secondly, combined with the special operating characteristics of electrical equipment, the path selection strategy is optimised to ensure that the optimal maintenance path can be quickly found even in highly dynamic changes. In addition, according to the actual needs of electrical system maintenance, the applicability and robustness of the algorithm in real-time data flow are improved. Therefore, it can better cope with sudden failures and changing operating conditions. These innovations not only make the algorithm perfect in theory but also shows its advantages in practical application, which has broad application prospect and practical value.

This study is divided into four parts. The first part is the ant colony algorithm and electrical equipment maintenance research status review. The second part is the construction of electrical equipment condition monitoring and predictive maintenance model based on optimised ant colony algorithm. The third part is model performance test and maintenance strategy feasibility simulation analysis. The fourth part is to summarise the research results and present the shortcomings of the research.

2. Related Works

ACO is a classic heuristic algorithm. Researchers have been committed to improving the performance and convergence speed of ACO to enhance the search capabilities. Wang *et al.* proposed a spatial mobile edge computing network architecture. An improved ant colony algorithm resource scheduling method based on this architecture is designed. The method optimises the pheromones and heuristic factors of ant colony algorithm by time delay and resource constraints. The roulette algorithm is used for route selection to avoid falling into local optimal. The introduced dynamic scheduling algorithm effectively reduces the task execution time. When the number of tasks reaches 200, the simulation results show that the proposed algorithm has obvious advantages in terms of execution time and resource utilisation compared with Min-Min algorithm and PSO algorithm. The application potential of ant colony algorithm in complex networks is verified [10]. Ashour *et al.* proposed a new mixed-integer nonlinear programming model, which is designed through a single-target, single-product, and multi-stage closed supply chain network. The often overlooked fixed transportation costs in distribution networks are given special consideration. This type of network design problem belongs to NP-hard problem. Therefore, this paper chooses ACO algorithm to solve the model. Compared with the accurate results, the proposed ACO algorithm shows high-quality effectiveness in solving wireless network design problems [11]. This paper aims to improve the transient stability of the solution model by applying the continuous ACO algorithm. According to the test results, compared with the traditional method, the continuous ACO algorithm can reduce the fuel cost of power system operation to $60,928.36/h, which is reduced by $15.33 / h. The standard deviation is $2.51 / h. The execution time is 7.66 s. This strategy can be applied to power system scheduling, which has higher efficiency than other traditional methods [12]. Kumara *et al.* proposed an adaptive routing algorithm based on the original ant colony algorithm. Compared with traditional routing algorithms, it is obvious that the proposed algorithm has better performance. It can effectively solve the premature convergence, counting to infinity and slow update encountered by distance vector routing algorithms. This indicates that ant colony algorithm has great advantages and potential in the application of route selection, providing a more efficient and stable solution for network routing [13]. Aiming at the communication delay between controllers and switches in traditional computer networks and the communication failure between controllers caused by network link failure, a dynamic controller placement method based on delay and load optimisation is proposed. In this paper, a multi-objective optimisation model based on link failure is constructed. A resource allocation method based on task delay and reliability constraints is proposed. Heuristic ant colony algorithm is used to solve the task completion delay and computational resource waste caused by uneven resource allocation in edge servers. Experimental results show that the proposed resource allocation algorithm has significant effects in optimising computing resources and reducing task completion delay. The ant colony algorithm has better computational results [14]. Aiming at the path planning problem for multi-unmanned ground vehicles, Liu *et al.* proposed a path planner for multi-unmanned vehicles based on continuous ant colony algorithm. Compared with other algorithms, the experimental results verify the superiority of this method in solving complex and high-dimensional problems [15].

With the development of the Internet of Things and artificial intelligence technology, intelligent maintenance has become an important direction of electrical equipment maintenance. Priyanka *et al.* adopted encryption technology for smart grid demand response security. A cryptographic model with robust authentication and routing model in smart grid is designed. The experimental results show that its performance is good [16]. Peter *et al.* developed standards for continuous thermal monitoring. The health status of monitoring device connections has been studied as an alternative method for infrared thermal imaging measurement. The findings show that the maintenance of electrical switchgear and motor control centres is critical to improving safety and ensuring uptime for all industry facilities [17]. Litherland *et al.* proposed an asset management framework to model degradation, failure, inspection, and maintenance of electrical units. Studies showed that this model can provide a basis for maintenance decisions, thus reducing the life cycle cost of electrical equipment [18]. Malafeev *et al.*

Table 1
Application Comparison of Different Optimal Ant Colony Algorithms

Researcher	Application field	Major improvement	Experimental result
Ghods M	Afforestation planning	Combined with 3D geographic information system	Five trees were planted at the south end of the building to achieve an area coverage of 88%
Wang Y	Mobile edge computing network architecture	Optimisation of pheromone and heuristic factor	When the number of tasks is 200, the execution time and resource utilisation are better than Min-Min and PSO algorithms
Ashour M	Supply chain network	ACO is used to solve NP-hard problems	High quality and efficiency to solve wireless network design problems
Moradi B	Power system dispatching	Continuous ant colony optimisation algorithm	Power system operating fuel costs decreased to $60,928.36/hour, a decrease of $15.33/hour
Kumara P	Computer network routing	Adaptive routing algorithm	The application in network routing has better performance
Li C	Computer network	Method based on delay and load optimisation	Optimise computing resources and reduce task completion delays
Liu J	Path planning	Multi-vehicle path planner is adopted	It has advantages in solving complex and high dimensional problems

proposed an algorithm for processing insulation resistance measurement data in power grids with isolated neutrals. The experimental results show that this scheme not only meets the requirements of normative documents for mining equipment but also improves the insulation resistance control program and electrical equipment protection speed [19]. Mingxing *et al.* proposed a new gate oxide monitoring method for SIC metal-oxide-semiconductor field-effect transistors. Experiments show that this monitoring method is applicable to different switching frequencies and load currents, which has strong practicability [20].

In summary, the main objective of this study is to develop an optimised ant colony algorithm to improve the accuracy and efficiency of electrical equipment status monitoring and predictive maintenance. Specifically, it aims to reduce the path length required for maintenance through algorithmic improvements, shorten failure response times, and reduce associated costs. Based on this objective, specific measures are adopted to optimise the pheromone updating process and introduce efficient routing strategies to improve the local search efficiency while maintaining the global search ability of the algorithm.

3. Construction of Electrical Equipment Condition Monitoring and Predictive Maintenance Model Based on OACA

When constructing the model, the operational data of the electrical equipment is first collected, followed by noise removal, data normalisation, and missing value processing. Next, corresponding improvements are made based on the shortcomings of traditional ACO, optimising the pheromone evaporation, and node jump methods.

3.1 Monitoring and Feature Extraction of Various Indicators for Electrical Equipment

The reliability of electrical equipment refers to the ability of the equipment to operate normally for a certain period of time without failure under specific operating conditions. Reliability is an important indicator for measuring equipment performance [21], [22]. It is also one of the key factors for the safe and reliable operation of electrical equipment, usually expressed as a failure rate function, as displayed in (1).

$$\lambda(t) = -R(t) \cdot \frac{\mathrm{dR}(t)}{\mathrm{dt}} \tag{1}$$

In (1), $\lambda(t)$ is the failure rate function. t is the usage time. $R(t)$ is the reliability function. The bathtub curve is a common curve shape that represents changes in system or equipment failure rates, as shown in Fig. 1.

In Fig. 1, the bathtub curve is usually divided into three stages, infancy, maturity, and wear and tear. During infancy, the failure rate shows a high initial value and gradually decreases over time. The failure rate will maintain a relatively low and stable level, which is called the mature stage. As the equipment runs for a long time, the components begin to wear and age. The failure rate gradually increases, indicating that the system or equipment has entered a wear period. The operational data of electrical equipment includes multiple indicators. The device status is represented by a time series, as shown in (2).

$$\Psi_i = \{I_i, V_i, T_i, F_i, S_i\} \tag{2}$$

In (2), I_i, V_i, T_i, F_i, and S_i, respectively, represent the current value, voltage value, temperature value, frequency

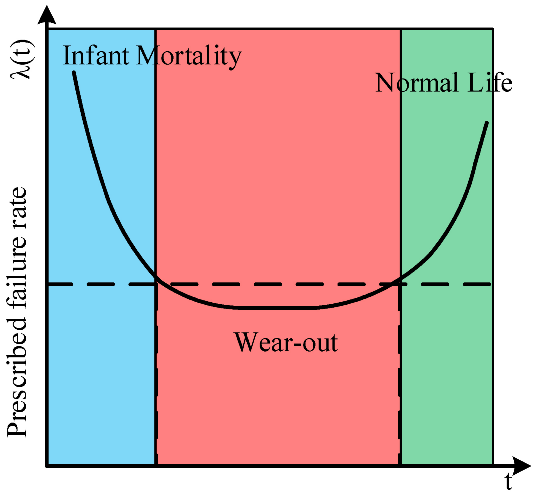

Figure 1. Electrical equipment failure rate change curve.

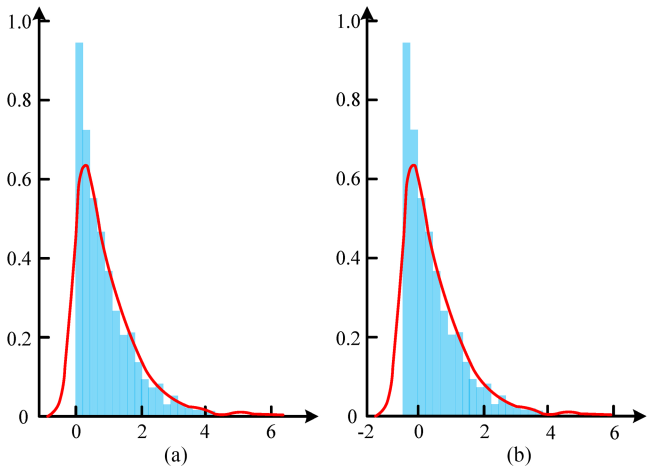

Figure 2. Distribution of normalised data.

value, and fault flag at the i-th time point. Filter is used to remove signal noise. The Kalman filter can estimate the true value of the signal and the covariance matrix of the noise, as shown in (3).

$$Y\left(i\right) = H\left(i\right) * \Psi\left(i\right) + K\left(i\right) * \left[Z\left(i\right) - H\left(i\right) * \Psi(i)\right] \quad (3)$$

In (3), $Y\left(i\right)$ represents the filtered value at the i-th time point. $H\left(i\right)$ represents the observation matrix. $K\left(i\right)$ is the Kalman gain. $Z\left(i\right)$ represents the observed value at the i-th time point. After denoising the original data, the data is Z-score normalised, as shown in (4).

$$\kappa = \frac{(Y_i - \mu)}{\sigma} \quad (4)$$

In (4), κ represents the normalised data. μ is the mean of the original data. σ is the standard deviation. The normalised data distribution is shown in Fig. 2.

From Fig. 2, Z-score normalisation transforms the raw data into standard normal distribution data with a mean of 0 and a standard deviation of 1. Meanwhile, the distribution shape of the data remains unchanged. The operation data of electrical equipment may lose values. Therefore, the interpolation method is adopted to fill in the missing data. Linear interpolation is used for the missing data points, as shown in (5).

$$a = b_1 + \left(\left(b_2 - b_1\right) * \left(c - c_1\right)\right) / \left(c_2 - c_1\right) \quad (5)$$

In (5), a represents the missing value. b_1 and b_2 represent the values of two adjacent known data points, respectively. c_1 and c_2 represent the positions of adjacent known data points, respectively. c represents the location of the missing value. After imputing missing values, whether the interpolated data meets the data distribution and other statistical characteristics is verified.

3.2 Finding the Optimal Path for Electrical Equipment Maintenance Based on Optimisation Ant Colony Algorithm

Electrical equipment maintenance requires a reasonable maintenance plan based on equipment importance, fault frequency, and availability of repair resources. Important equipment, frequently malfunctioning equipment, and equipment with safety risks are prioritised. The maintenance path of general electrical equipment is solved using the shortest path algorithm in graph theory, as shown in Fig. 3.

In Fig. 3, the blue circle represents a low failure rate device. Yellow indicates a medium failure rate device. Red indicates a high failure rate device. Figure 3(a) shows the general inspection path without fault rate classification. The shortest path between adjacent devices is used for inspection, so the path at this time is the optimal path. Figure 3(b) shows the inspection path after adopting fault rate classification. Important and high failure rate equipment needs to be prioritised. Therefore, compared to the general path, the growth of the inspection path is significant. It greatly increases the cost and time of inspection. For the path selection after fault classification, traditional ant colony algorithm calculates the probability of each device, and then marks this point as a taboo point until a complete path is established. The jump probability at each device is shown in (6).

$$P_{\mathrm{ij}}^{k} = \begin{cases} \frac{\tau_{\mathrm{ij}}^{\alpha}(t)\eta_{\mathrm{ij}}^{\beta}}{\sum \tau_{\mathrm{iu}}^{\alpha}(t)\eta_{\mathrm{iu}}^{\beta}}, & j \in d_k, u \in d_k \\ 0, & \text{else} \end{cases} \quad (6)$$

In (6), P_{ij}^{k} is the probability that Ant k jumps from i to j. $\tau_{\mathrm{ij}}\left(t\right)$ is the pheromone concentration of path (i, j) at t. η_{ij} is heuristic information on the path. After all ant paths are established, the path length obtained by the ants is calculated. The shortest path length and corresponding path are recorded, as shown in (7).

$$\tau_{\mathrm{ij}}\left(t+1\right) = \left(1-\rho\right)\tau_{\mathrm{ij}}\left(t\right) + \sum_{k=1}^{m} \Delta\tau_{\mathrm{ij}}^{k} \quad (7)$$

In (7), $\tau_{\mathrm{ij}}\left(t+1\right)$ and $\tau_{\mathrm{ij}}\left(t\right)$ are the pheromone concentrations on the path at $(t+1)$ and t, respectively. $\Delta\tau_{\mathrm{ij}}^{k}$ is the increment of pheromones. After recording the path, the pheromones on the path are updated, as shown

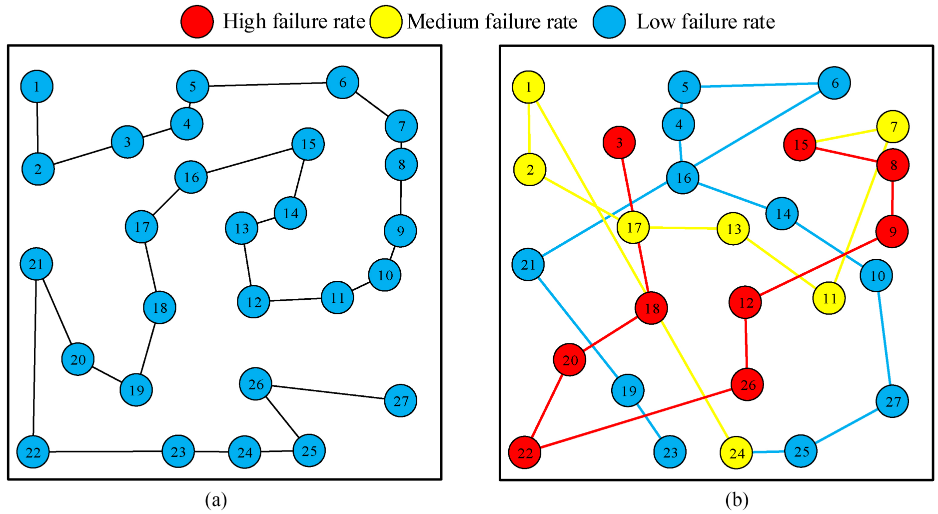

Figure 3. Electrical equipment inspection paths under shortest path algorithm: (a) general overhaul path and (b) overhaul route after fault classification.

in (8).

$$\Delta\tau_{\mathrm{ij}}^{k}=\begin{cases} Q/L_k, & \text{the kth ant passes through arc}(i,\ j)\\ 0, & \text{other}\end{cases} \tag{8}$$

In (8), Q represents the total amount of pheromones released by each ant during the path finding process. L_k is the length of the path found by the ant. The process based on ACO electrical equipment inspection path is displayed in Fig. 4.

In Fig. 4, the ant colony is first initialised, and then an initial pheromone concentration is assigned to each edge. Next, each ant uses the selection probability equation to select the next node. After completing a patrol path, the pheromone concentration on the passed path is updated based on the quality of the patrol path. The quality of the inspection path in the current ant colony is compared with the global optimal solution. Then, the global optimal solution is updated. The above steps are repeated until the stop conditions are met. Finally, the optimal inspection path, *i.e.,* the optimal inspection path for electrical equipment, is obtained. However, in practical applications, this method has low efficiency and unsatisfactory results, so it is optimised. After optimisation, the ant colony system adopts a pseudo random proportional state transition rule, as shown in (9).

$$j=\begin{cases}\operatorname{argmax}\left\{\tau\left(\mathrm{iu}\right)^{\alpha}\eta\left(\mathrm{iu}\right)^{\beta}\right\}, & q\le q_0\\ S, & \text{other}\end{cases}\tag{9}$$

In (9), j is the jump node selected by the ant at node i. q_0 is a given parameter between [0,1]. q is a random number that follows a uniform distribution between [0,1]. When ants choose to skip nodes, a random number q is generated. If $q \le q_0$, the ant selects the node with the maximum parameter $\tau\left(\mathrm{iu}\right)^{\alpha}\eta\left(\mathrm{iu}\right)^{\beta}$ to jump. In addition, the optimised ant colony system adopts local pheromone and global pheromone to update. The local pheromone is

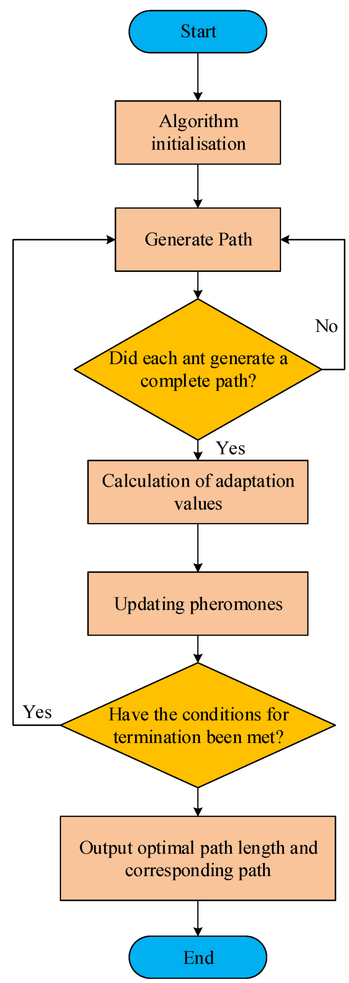

Figure 4. Flowchart of optimal inspection path for ant colony algorithm.

updated after the ant selects the jump node, as shown in (10).

$$\tau_{\mathrm{ij}}\leftarrow\left(1-r\right)\tau_{\mathrm{ij}}+r\Delta\tau_{\mathrm{ij}}\tag{10}$$

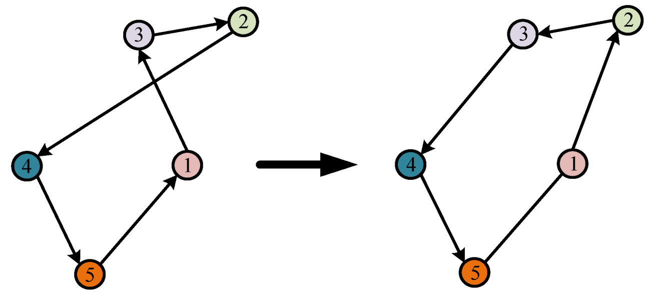

Figure 5. Localised pheromone evaporation path search.

In (10), $r \in [0, 1]$ is the local pheromone evaporation factor. After using local pheromone evaporation, the local path search is shown in Fig. 5.

In Fig. 5, an unoptimised sub path is given, which includes nodes 1, 2, 3, 4, and 5. The initial path is $D \rightarrow 1 \rightarrow 3 \rightarrow 2 \rightarrow 4 \rightarrow 5$. Two nodes in the path are selected, such as node 1 and node 4. The path between these two nodes is reversed. After reversing the path, the new path is $1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5$. According to the triangular inequality, the length of the new path is shorter than the original path. Therefore, a more optimal path is obtained. The updated global pheromone is shown in (11).

$$\tau_{\mathrm{ij}} \leftarrow (1-\omega)\,\tau_{\mathrm{ij}} + \omega\Delta\tau_{\mathrm{ij}} \tag{11}$$

In (11), $\omega \in [0, 1]$ is the global pheromone evaporation factor. $(1-\omega)$ is the retention coefficient of global pheromones. The updated pheromone is shown in (12).

$$\Delta\tau_{\mathrm{ij}} = \begin{cases} 1/L_{\mathrm{gb}},\ (i,j) \in \text{globally optimal path} \\ 0, \qquad \text{other} \end{cases} \tag{12}$$

In (12), L_{gb} is the current optimal path length. The pheromone gap between the optimal path and other paths increases, leading to algorithm stagnation. Therefore, the sigmoid function is introduced to perturb pheromones, as shown in (13).

$$f(x) = \frac{1}{e^{-x}+1} \tag{13}$$

In (13), $f(x)$ is the probability of pheromone perturbation. x is the population size. The pheromone concentration after disturbance is shown in (14).

$$\tau_{\mathrm{ij}} = \frac{1}{e^{-\tau_{\mathrm{ij}}+\mathrm{mean}(\tau)}+1} \tag{14}$$

In (14), $\mathrm{mean}(\tau)$ is the mean of the pheromone matrix. To improve the exit mechanism of pheromones, adaptive adjustments are made to the pheromone evaporation factor, as shown in (15).

$$\rho = \frac{L_{\mathrm{mean}} - L_{\mathrm{min}}}{L_{\mathrm{min}}} \tag{15}$$

In (15), L_{mean} is the average length of the iteration path. L_{min} is the shortest path length in iteration path. The optimal inspection path for electrical equipment solved by OACA is displayed in Fig. 6.

From Fig. 6, the optimised ant colony algorithm first determines the inspection nodes and targets. Then, the problem is abstracted as the distance between each node, representing the distance consumption. Initialising pheromones affects the probability of ants choosing paths. Next, the ant selects the next mobile node based on the pheromone value and heuristic function, and selects a path and updates the pheromone according to certain rules. After all ants complete a cycle, the pheromone values are updated based on the path and quality evaluation. Ant movement and pheromone updating are repeated until the termination condition is met. Finally, the path with the best path quality evaluation is selected as the optimal inspection path. τ is the pheromone intensity. ρ is the pheromone evaporation rate. $\Delta\tau$ is an increase in pheromones.

In this paper, the objective function of optimised ant colony algorithm is designed to minimise inspection path length and maintenance cost. The objective function is defined, as shown in (16).

$$f(x) = \alpha \sum d_i + \beta \sum c_i \tag{16}$$

In (16), d_i is the inspection distance of the corresponding equipment. c_i is the maintenance cost after the corresponding equipment malfunctions. α and β are the weight coefficients.

In general, this study continuously monitors the health status of electrical equipment for predictive maintenance. For electrical equipment, the physical quantities that usually need to be monitored include current, voltage, temperature, and frequency, *etc.* Abnormal changes in these parameters are early signals that the equipment is about to fail. This study collects these parameter values during device operation. These collected data are analysed to evaluate the health status of the equipment and determine preventive maintenance plans. If the device parameter value exceeds the preset normal range or the change trend indicates that the device may be about to fail, corresponding maintenance operations need to be carried out to ensure the stable operation of the power system after the fault occurs.

To improve the efficiency and effect of electrical equipment status monitoring and predictive maintenance, the method based on optimal ant colony algorithm (OACA) is adopted in this study. This method optimises the traditional ant colony algorithm, which can deal with the condition monitoring and predictive maintenance more effectively. Based on the method proposed in this study, the optimal maintenance strategy can be found in a very short time, thus greatly improving the equipment maintenance efficiency and reducing the maintenance cost.

In this paper, a number of quantitative indicators are introduced to comprehensively evaluate and compare the efficiency of the proposed electrical equipment maintenance strategy. These metrics are as follows. Fault detection rate, it is used to measure the model's ability to detect potential faults during the monitoring process. Maintenance response time, it refers to the time required from fault detection to fault response. Cost-efficiency

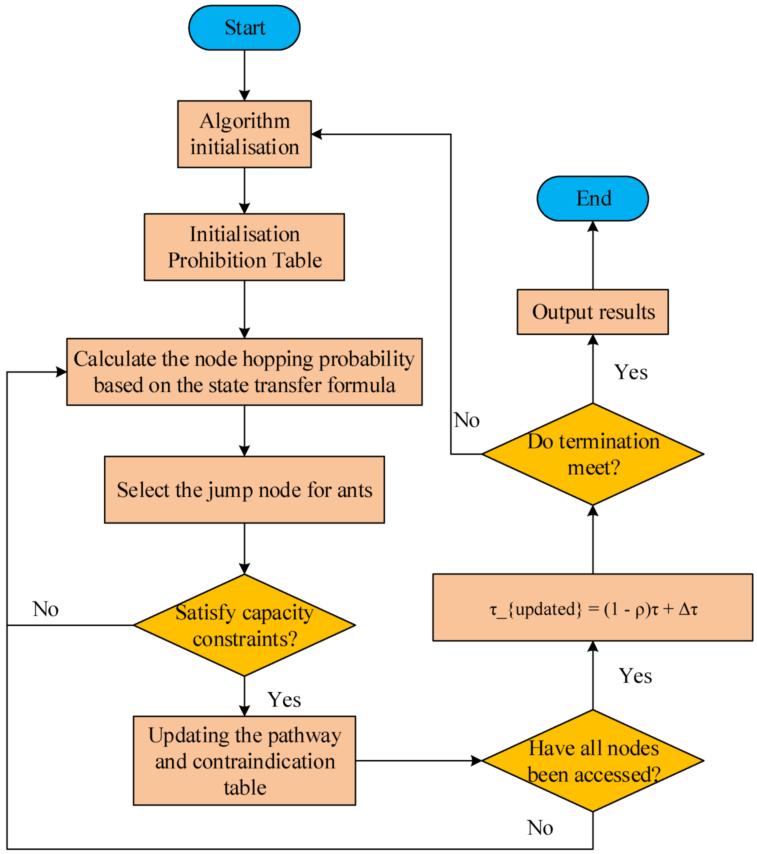

Figure 6. Flowchart of the optimal inspection path of the optimised ACO algorithm.

analysis, the ratio of the preventive maintenance total cost to the emergency maintenance cost avoided by identifying faults in advance. The fault detection rate is calculated by dividing the number of faults actually detected by the total faults that occur, providing a way to measure the model accuracy. Maintenance response time is measured by recording the time required from the fault alarm to the completion of maintenance tasks. Cost-benefit analysis is evaluated based on predictive maintenance versus actual maintenance costs to show the ability to maximise equipment uptime and reliability within the operational budget. These indicators have significant impacts on the analysis results. They can not only quantify the actual effectiveness of maintenance strategies but also provide decision-making tools with data support for equipment managers. Determining the exact values of these indicators requires statistical analysis of long-term operational data of electrical equipment, as well as simulation tests to optimise the ant colony algorithm operation under different maintenance plans and strategies. In this way, the policy parameters can be adjusted regularly to adapt to the operating conditions. The maintenance plan can be continuously optimised.

4. The Performance Testing and Feasibility Simulation Analysis of Maintenance Strategies for Models

For the condition monitoring model, various parameters and operating status data of electrical equipment are collected. The performance of the model is evaluated by comparing the ACO, GA, and OACA. The feasibility of maintenance strategies based on OACA is evaluated through simulation analysis. Firstly, a simulation model of the electrical system is established, incorporating the effects of faults and random events into the model. Then, the maintenance strategy based on OACA is compared with the traditional periodic inspection method to evaluate the optimisation effect.

4.1 Performance Testing and Comparative Analysis of Different Algorithms

In the experiment, annual inspection data from an electrical company in 2018 are used. These data sets include maintenance records, fault reports, and inspection reports of various electrical equipment. In this study, the electrical equipment used includes equipment with different functions and specifications, such as high-voltage transformers, transmission lines, distribution equipment, and various types of control and protection equipment. For example, the high voltage transformer is HV-XX220/110. The transmission line is a commercially available transmission cable designed for extremely high voltage power transmission with a voltage rating of up to 500 kV. Distribution equipment, such as low-voltage distribution cabinets in distribution rooms are also collected. The source is commercially available. The technical specifications include rated working voltage 380 V. These devices are based on their extensive application

Table 2
Experimental Environment and Parameters

Experimental environment/Parameter name	Hardware parameters/ or Environment name
CPU	Xeon (R) Silver 4214@2.20ghz*24
GPU	NVIDIA Geforce RTX 3060 Ti
RAM	32G
Load factor weights	5
Pheromone perturbation probability	0.7
Pheromone importance factor	1
Heuristic information importance factor	3
Species population size	300
Total pheromones	100
Maximum Number of Iterations	200

Table 3
Performance Comparison Between Traditional Ant Colony Algorithm and Optimised Ant Colony Algorithm

Index	Traditional ant colony algorithm	Optimize ant colony algorithm	Percentage improvement
Average solution time (seconds)	120	80	0.3333
Average path length (km)	80	60	0.25
Failure response time (minutes)	45	30	0.3333
Cost savings (monetary units)	1,000	1,400	0.4
Number of iterations	150	100	0.3333
Fault detection rate (%)	75	90	0.2

in modern power grids. The experimental environment and parameters are shown in Table 2.

In Table 2, adjusting these parameters can optimise the execution of the algorithm for better results. In the experimental setup, a series of key parameters are carefully set to adjust and optimise the performance of the ant colony algorithm. Load factor weights are factors that determine the priority of electrical equipment. Their values are determined based on the equipment's role in the grid and the urgency of maintenance. The pheromone perturbation probability is used to introduce the explorative nature of the algorithm. It is set to balance exploration and exploitation, so that the algorithm can effectively jump out of the local optimal solution. Heuristic information importance factors influence the ants' decision process to choose the next path. Their adjustments are based on prior knowledge of the path length and quality. During the experiment, these parameters are dynamically adjusted and updated to fit the characteristics of the data set and optimisation objectives.

To analyse the application effect of optimised ant colony algorithm in condition monitoring and predictive maintenance, a series of experiments are carried out to collect key statistical data. Given a certain number of electrical equipment, the traditional ant colony algorithm and the optimised ant colony algorithm are used to calculate and compare their performance in fault detection and inspection path optimisation. The experimental data in Table 3 shows the improvement degree of the optimisation algorithm in different performance indexes.

Table 3 shows the comparison results of traditional ant colony algorithm and optimised ant colony algorithm in multiple maintenance performance indexes. From the average solution time, the optimisation algorithm is 33.33% faster than the traditional algorithm, thus improving the computational efficiency. In terms of path optimisation, the optimisation algorithm reduces the average path length by 25%, meaning that maintaining the path is more efficient and economical. The fault response time has significantly decreased by 33.33%, reflecting the faster processing ability after the fault occurs. In terms of cost savings, this optimisation algorithm saves 40% of maintenance costs compared to traditional algorithms, which shows the potential of the optimisation algorithm in reducing operating costs. The number of iterations is reduced by 33.33%, which shows the convergence speed

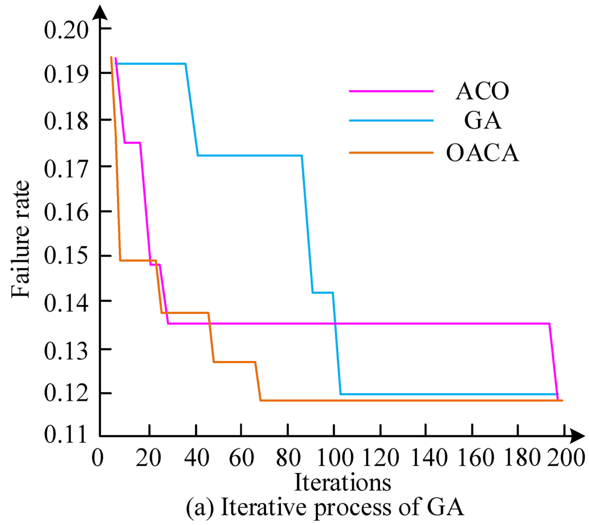

Figure 7. Iterative results of monitoring failure rates for different algorithms.

of the optimisation algorithm is improved. Finally, the fault detection rate is increased by 20%, which proves the effectiveness of the optimisation algorithm in the prediction accuracy.

The iterative results of monitoring failure rates for different algorithms are shown in Fig. 7.

In Fig. 7, The horizontal and vertical axes represent the map coordinates of the inspection points. The model performance evaluation includes ACO, genetic algorithm (GA), and OACA. The GA achieves the optimal monitoring fault rate iteration result of 0.121 after 100 iterations. The optimal value of the ACO in 193 iterations is 0.142. The OACA reaches the optimal value of 0.136 after 67 iterations. From the results, ant colony algorithm performs better than GA in solving the monitoring fault rate. It can find a lower optimal solution. The OACA further enhances efficiency and performance, which can find nearly optimal solutions in fewer iterations. The inspection path planning results of different algorithms are shown in Fig. 8.

In Fig. 8, the horizontal and vertical axes are the map coordinates of the inspection points. The total path length of the GA in planning inspection paths is 814 km. In contrast, the total path length of the ACO is 598 km. The total path length of the OACA is only 400 km. This indicates that ACO and OACA can achieve more optimised and compact results when planning inspection paths. Specifically, the GA has a path length of 417 km at high failure rate inspection points, 173 km at medium failure rate inspection points, and 224 km at low failure rate inspection points. In contrast, the ant colony algorithm has a path length of 278 km at high failure rate inspection points. The path length of the inspection point with medium failure rate is 137 km. The path length at low failure rate inspection points is 183 km. The OACA has a path length of 203 km at high failure rate inspection points. The path length of the inspection point with medium failure rate is 26 km. The path length at low failure rate inspection points is 171 km. The OACA is superior to GA and ordinary ACO. It can obtain shorter path lengths during inspection path planning. This indicates that optimised ant colony algorithm can better optimise path planning, save inspection costs, and time.

4.2 Evaluation of the Effectiveness for Optimised Ant Colony Algorithm and Improvement of Inspection Strategy

Based on the actual structure and parameters of the electrical system, a simulation model that can simulate the electrical system operation is established. The model includes components, such as power stations, transformers, transmission lines, and distribution lines. The effects of faults and random events are introduced into the simulation model to simulate faults, fault recovery, random events, and other situations that occur during the operation of electrical systems. The inspection path length for OACA model iteration under different fault increase rates is shown in Fig. 9.

According to Fig. 9, under different fault increase rates, the optimal inspection path length after optimising the ant colony algorithm iteration can be observed. When the fault increase rate is 20%, the path length is 776 km. When the fault increase rate is 30%, the path length is 843 km. When the fault increase rate is 40%, the path length is 847 km. When the fault increase rate is 50%, the path length is 847 km. Within the range of 20% to 50% increase in fault rate, the optimised ant colony algorithm can find better inspection paths than traditional regular inspection methods. According to the traditional sequential inspection path strategy, the total length of the inspection path is 1,100 km. This means that the traditional periodic inspection method requires a longer path to complete the inspection task at all fault increase rates. The electrical equipment maintenance cost before and after path optimisation is shown in Fig. 10.

From Fig. 10, before path optimisation, the cost of device A ranges from 51.4% to 72.1%. The equipment B ranges from 34.2% to 40.4%. The equipment C ranges from 29.8% to 56.3%. The cost equipment D ranges from 32.3% to 36.1%. The equipment E ranges from 12.6% to 14.5%. However, after path optimisation, the cost of device A decreases to between 30.6% and 39.4%. The equipment B decreases to between 28.1% and 34.6% in the optimised path. The equipment C decreases to between 4.3% and 27.1% in the optimised path. The equipment D ranges from 27.4% to 32.3%. The equipment E decreases from 6.9% to 11.3% in the optimised path. In summary, after path optimisation, the proportion of cost for equipment A, C, and E significantly is decreased. The proportion of cost for equipment B and D has not changed much or slightly decreased. This optimisation balances the total cost, helping to improve efficiency and reduce operating costs. The relationship between the repeated fault detection points and the total detection points before and after the optimisation is shown in Fig. 11.

From Fig. 11, before optimising the inspection path, the detection variance of high failure rate equipment is 3.21, the detection variance of medium failure rate

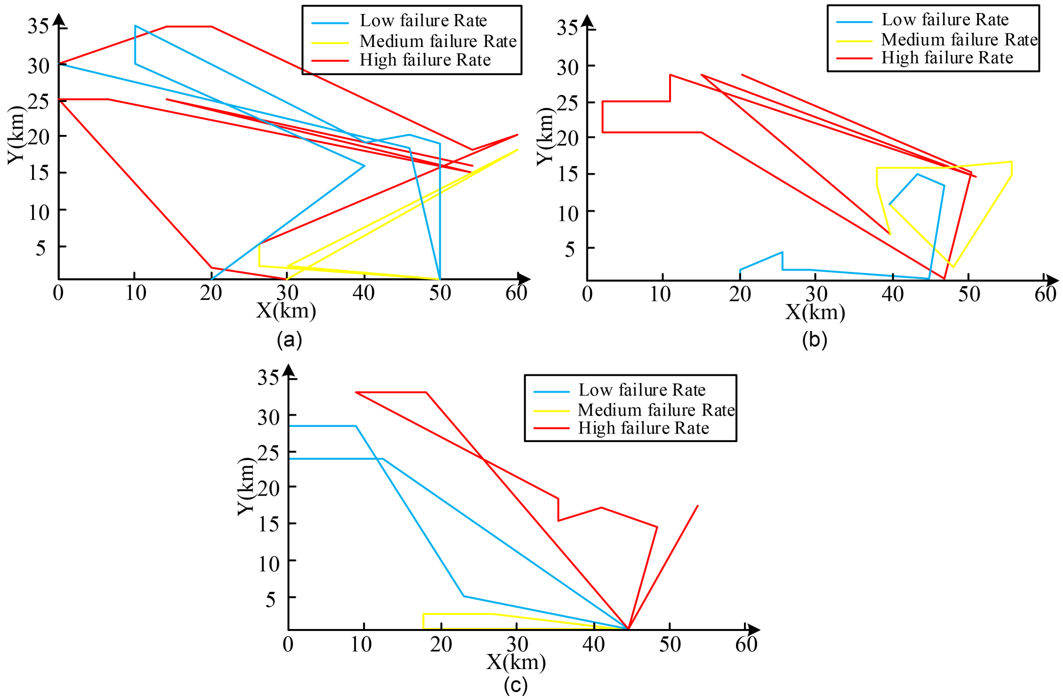

Figure 8. Patrol road force planning results for different algorithms: (a) path planning of the GA; (b) path planning of the ACO; and (c) path planning of the OACO.

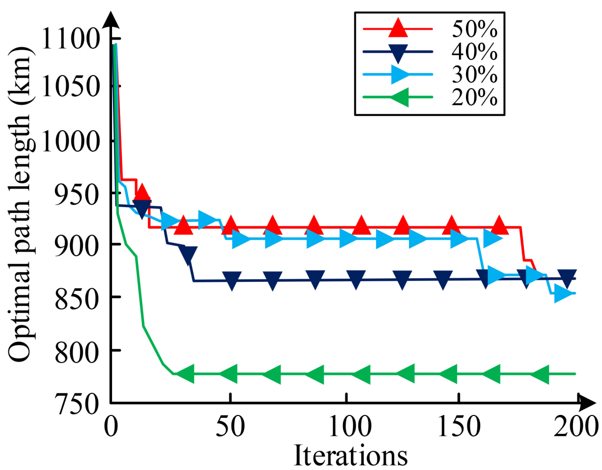

Figure 9. Results of model iterations of the optimised ant colony algorithm for different fault increase rates.

equipment is 4.46, and the detection variance of low failure rate equipment is 13.26. According to the results, before optimising the inspection path, there is a significant difference in the dispersion of inspection volume for devices with different failure rates. The detection variance of low failure rate devices is the largest, indicating that some resources may be wasted on these relatively stable devices. After path optimisation, the detection variance of high failure rate equipment decreases to 1.14. The detection variance of medium failure rate equipment decreases to 0.97. The detection variance of low failure decreases to 1.25. Path optimisation significantly improves the dispersion of inspection volume, especially for equipment with medium and low failure rates. During the inspection process, the difference between the repeated fault detection points of high, medium, and low fault rate equipment and the actual fault detection points decreases. This means that the equipment repetition with different failure rates during the inspection process is reduced. The resource utilisation efficiency is improved.

5. Conclusion

The importance of electrical equipment in industrial production and the impact of failure on production efficiency and safety are significant. Therefore, it is essential to develop an effective condition monitoring and maintenance strategy. The purpose of this study is to solve the resource inefficiency and maintenance blindness in the traditional electrical equipment condition monitoring and predictive maintenance strategy. Based on optimised ant colony algorithm, a new electrical equipment monitoring framework and maintenance process are constructed. The ant colony algorithm, which includes dynamic pheromone updating and heuristic search optimisation, is used in this study. The performance of the algorithm before and after optimisation is compared through experimental simulation. In the iteration process, the optimisation algorithm reaches the optimal value of 0.136 after 67 iterations. Within the failure rate range of 20%–50%, the inspection path length can be effectively reduced. This is reflected in the path reduction of high-failure rate devices to 203 km, medium-failure rate devices to 26 km, and low-failure rate devices to 171 km. Compared with other algorithms, this algorithm can reduce the cost and improve the efficiency of resource utilisation. However, there are some limitations in this paper. Although the proposed optimisation algorithm

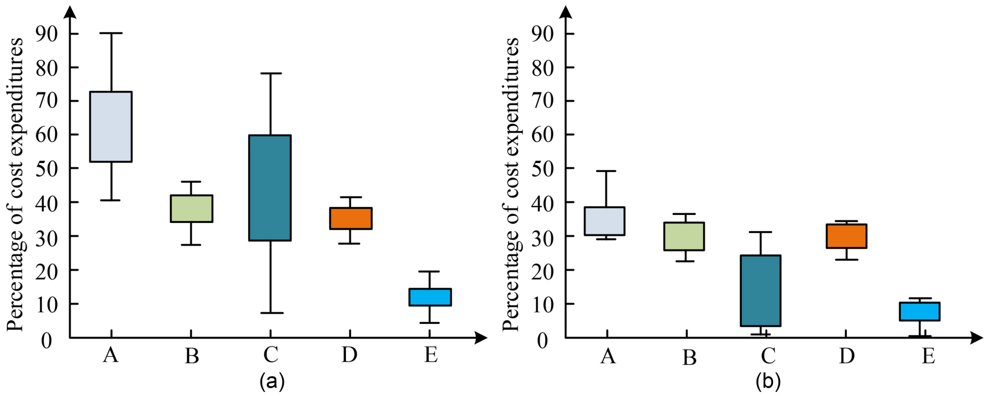

Figure 10. Percentage of maintenance costs for electrical equipment before and after route optimisation: (a) before route optimisation and (b) after route optimisation.

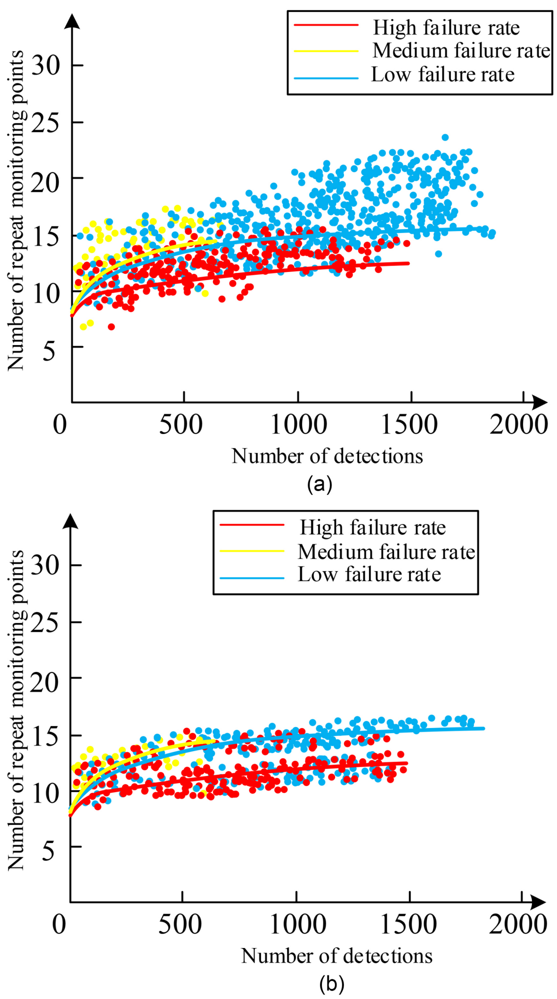

Figure 11. Distribution of repeat fault detection points before and after path optimisation: (a) before optimisation and (b) after optimisation.

performs well in simulation experiments, the actual electrical equipment environment is more complex and variable, involving more factors, such as fault identification, response speed, maintenance resource allocation, *etc*. The effectiveness of the algorithm in real-world applications still needs to be verified in a wider range of real-world conditions. In addition, the computational complexity of the algorithm and its applicability to large-scale systems are also the directions that need to be further explored in future research.

Appendix

Table A
Term List

Terminology	Definition
ACO (Ant colony optimisation)	An optimisation algorithm that simulates the foraging behaviour of ants in nature.
GA (Genetic algorithm)	A search heuristic algorithm based on natural selection and genetics to solve optimisation and search problems.
OACA (Optimised ant colony algorithm)	An optimised version of the traditional ant colony algorithm designed to improve its performance and efficiency.
Fault detection rate	Used to measure the frequency at which the fault prediction system correctly identifies fault instances.
Maintenance response time	The time elapsed between the system detecting a potential fault and the system starting to respond to the expected fault.

References

[1] P. Faghihi and A. Jalali, An artificial neural network-based optimization of reverse electrodialysis power generating cells using CFD and genetic algorithm, *International Journal of Energy Research, 15*(46), 2022, 21217–21233.

[2] Y.H. Chae, C.Y. Lee, S.M. Han, and P.H. Seong, PHSAP, Graph neural network based multiple accident diagnosis in nuclear power plants: Data optimization to represent the system configuration, *Nuclear Engineering and Technology, 54*(8), 2022, 2859–2870.

[3] D. Jaraniya and S. Kumar, Integration of charging station to the smart grid power network by using robust immune feedback adaptive and Rao optimization approaches, *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields, 5*(36), 2023, 1–16.
[4] S. Chen, W. Hu, Y. Du, S. Wang, C. Zhang, and Z. Chen, Three-stage relaxation-weightsum-correction based probabilistic reactive power optimization in the distribution network with multiple wind generators, *International Journal of Electrical Power and Energy Systems, 141*, 2022, 1–11.
[5] K. Shantanu, A.S. Ahmed, D. Narottam, and I. Syed, Reverse blocking over current busbar protection scheme based on IEC 61850 architecture, *IEEE Transactions on Industry Applications, 59*(2), 2023, 2225–2233.
[6] M.F. Sohail, C.Y. Leow, and S.H. Won, A Cat swarm optimization based transmission power minimization for an aerial NOMA communication system, *Vehicular Communications, 33*, 2022, 1–12.
[7] S.A. Kumar, S. Padma, and S. Madhubalan, Distribution network reconfiguration using hybrid optimization technique, *Tech Science Press, 33*(2), 2022, 777–789.
[8] Y.H. Jiang, H. Liu, J. Qu, and J. Chang, Energy-storage and reactive-power optimization of a high-proportional new energy distribution network considering voltage quality and flexibility, *Electric Power Construction, 44*(9), 2023, 68–79.
[9] M. Xu, C. Ma, and X. Han, Influence of different optimization algorithms on prediction accuracy of photovoltaic output power based on BP neural network, *Proc. 2022 41st Chinese Control Conf. (CCC)*, Hefei, 2022, 7275–7278.
[10] Y. Wang, J. Liu, Y. Tong, Q.W. Yang, Y.Y. Liu, and H.B. Mou, Resource scheduling in mobile edge computing using improved ant colony algorithm for space information network, *International Journal of Satellite Communications and Networking, 41*(4), 2023, 331–356.
[11] M. Ashour, R. Elshaer, and G. Nawara, Ant colony approach for optimizing a multi-stage closed-loop supply chain with a fixed transportation charge, *Journal of Advanced Manufacturing Systems, 21*(3), 2022, 473–496.
[12] B. Moradi, A. Kargar, and S. Abazari, Transient stability constrained optimal power flow solution using ant colony optimization for continuous domains (ACO_R), *IET Generation, Transmission and Distribution, 16*(18), 2022, 3734–3747.
[13] P. Kumara, S. Mahajanb, P. Srivastavab, K. Sharma, and P. Kaur, A novel ant colony optimization based intelligent routing algorithm, *International Journal of Computational Intelligence Research, 19*(1), 2023, 15–26.
[14] C. Li, K. Jiang, and Y. Luo, Dynamic placement of multiple controllers based on SDN and allocation of computational resources based on heuristic ant colony algorithm, *Knowledge-Based Systems, 241*, 2022, 108330.1–108330.19.
[15] J. Liu, S. Anavatti, M. Garratt, and H.A. Abbass, Modified continuous ant colony optimisation for multiple unmanned ground vehicle path planning, *Expert Systems With Applications, 196*, 2022, 1–15.
[16] C.N. Priyanka and N. Ramachandran, Analysis on secured cryptography models with robust authentication and routing models in smart grid, *International Journal of Safety and Security Engineering: An interdisciplinary Journal for Research and Applications, 13*(1), 2023, 69–79.
[17] B. Peter and F. Leija, Developing an IEEE continuous thermal monitoring standard and a major company's protection of their electrical assets: Exploring continuous thermal monitoring for electrical connections and components, *IEEE Industry Applications Magazine, 29*(2), 2023, 32–38.
[18] J. Litherland and J. Andrews, A Petri net asset management framework for railway switches and crossings, *Proceedings of the Institution of Mechanical Engineers, Part F. Journal of Rail and Rapid Transit, 237*(3), 2023, 322–334.
[19] S.I. Malafeev and S.S. Malafeev, Insulation resistance monitoring in an electrical network with an isolated neutral: Data processing in a device with impulse test voltage, *Russian Electrical Engineering, 94*(1), 2023, 13–18.
[20] M.X. Du, G.X. Yang, Z.H. Ren, and C.P. Chu, Degradation monitoring of SiC MOSFET gate-oxide based on differential mode conducted interference spectrum, *Microelectronics and Reliability, 140*, 2023, 1–10.
[21] W. Huang, T. Zhang, and X. Yao, Optimization for sequential communication line attack in interdependent power-communication network, *Physica A: Statistical Mechanics and its Applications, 592*, 2022, 1–15.
[22] J. Yu, R. Wang, and J. Wu, QoS-driven resource optimization for intelligent fog radio access network: A dynamic power allocation perspective, *IEEE Transactions on Cognitive Communications and Networking, 1*(8), 2022, 394–407.

Biographies

Jing Li received the M.Eng. degree in control engineering from Shanghai, Dong Hua University in 2020. She is working as an Experimental Teacher with the Mechanical and Electrical College, Shanghai Jianqiao University. She has repeatedly guided college students' innovation and entrepreneurship training programs, leading them to achieve outstanding results in competitions such as "Internet+", "Challenge Cup", and "Energy Conservation and Emission Reduction". Additionally, she is actively involved in developing the textbook "Programmable Controller Application Technology". Her research interests include control engineering, electrical engineering, and automation control.