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Path Planning Method for Distribution Network Based on Artificial Intelligence and Optimization Algorithms

Longfei Ma[1,*], Jiani Zeng[1], Baoqun Zhang[1], Ran Jiao[1] and Cheng Gong[1]
[1] State Grid Beijing Electric Power Company, Beijing, 100031, China
Corresponding authors: (e-mail: oldold2028@163.com).

Abstract This article explored a distribution network path planning method based on artificial intelligence (AI) and optimization algorithms (OAs) to solve multiple problems in traditional research. Traditional methods have limited effectiveness in dealing with complex network structures and dynamic load changes, high computational complexity, and low energy utilization efficiency. To address these challenges, firstly, multiple algorithms were compared and analyzed, and genetic algorithm was identified as the main OA, combined with PSO's (Particle Swarm Optimization) local search capability for hybrid optimization. Then, this article designed a distribution network path planning strategy based on real-time data and intelligent algorithms, aiming to improve the efficiency of power transmission and energy utilization, and reduce system operating costs. By flexibly adjusting and dynamically optimizing, the distribution network can respond more quickly to changes in load demand, enhancing the overall response capability and stability of the system. In addition, this article also focused on improving the security and reliability of the system, especially whether it can quickly make adaptive adjustments and response measures in the face of emergencies or abnormal situations, in order to ensure the continuous stability of the power grid operation. Finally, the actual effectiveness and application potential of AI and OA in distribution network path planning can be verified. By introducing AI and OA such as genetic algorithm and PSO, significant improvements have been made in the transmission efficiency of distribution networks. Specifically, after optimization, the average transmission efficiency increased by about 0.15%, with an improvement rate of about 21.43%. The total network loss was significantly reduced, with an average reduction rate of about 33.33%. The system's responsiveness and stability have been improved, and the optimized data is more centralized and stable. The effectiveness of OAs in reducing operating costs and emphasizing their role in improving the economic efficiency of the power system.

Index Terms Artificial Intelligence and Optimization Algorithms, Distribution Network Path Planning, Genetic Algorithm, Particle Swarm Optimization, Deep Reinforcement Learning

I. Introduction

In today's society, as one of the infrastructure, the operational efficiency and stability of the power system are crucial to the socio-economic operation. The efficient supply of electricity directly affects the overall industrial production, residents' lives, and economic development. However, traditional distribution network path planning methods are inadequate when facing complex network structures and dynamic load changes. Traditional methods are often based on static models or simple heuristic algorithms, which cannot effectively address the challenges brought by the complexity of network structures and load fluctuations. These methods have high computational complexity and low energy utilization, which hinders the further optimization and intelligent development of the power system. Therefore, how to use advanced AI and OA to improve the path planning of distribution networks has become one of the current research focuses.

Researchers have attempted to propose various methods to plan the paths of distribution networks. Wang J proposed a novel optimal path planning algorithm based on Convolutional Neural Network (CNN), namely NRRT * (Neural Rapidly-exploring Random Tree, NRRT). NRRT* utilizes the non-uniform sampling distribution generated by the CNN model. This model is trained using a large number of successful path planning cases [1]. Karur K used path planning algorithms to determine the safe, efficient, collision free and lowest cost travel path for mobile robots, unmanned aerial vehicles and autonomous vehicle from the origin to the destination. Choosing appropriate path planning algorithms can help ensure safe and effective point-to-point navigation [2]. Chen J studied the coverage path planning problem of autonomous heterogeneous unmanned aerial vehicles over a limited area. He proposed an accurate formula based on mixed integer linear programming using separated regions and heterogeneous drone models to fully search the solution space and generate the optimal flight path for autonomous drones, and designed an original algorithm based on clustering. He divided the area into clusters and obtained the approximate optimal point-to-point path of the drone, thus correctly and efficiently executing the coverage task. Random generated regions can be used for experiments to demonstrate the efficiency and effectiveness of the proposed method [3]. Schmid L introduced a new RRT* heuristic online information path planning algorithm. He used this method to continuously expand a candidate trajectory tree and reconnect nodes to maintain the tree and optimize intermediate paths. This enables the algorithm to achieve global coverage and maximize the utility of the path in the global environment using a single objective function [4]. Hayat S incorporated communication into the multi drone path planning problem for search and rescue missions, to achieve dynamic task allocation through information dissemination [5]. Li W conducted a comprehensive review of intelligent OAs. Learning-based Intelligent Optimization Algorithm (LIOA) refers to intelligent OAs with certain learning abilities. It is a traditional intelligent OA that combines learning operators or specific learning mechanisms to endow itself with certain learning abilities, thereby achieving better optimization behavior [6]. Gad A G introduced one of the most popular SI paradigms (Standard International Form), namely the PSO algorithm, which involves some technical features, including accuracy, evaluation environment, and proposed case studies, to study the effectiveness of different PSO methods and applications [7]. OA-based on mathematical programming often face problems such as slow convergence speed, locally optimal solutions, and insufficient response to dynamic load changes [8]-[10]. These limitations limit the further improvement of the overall efficiency and reliability of the power system, and there is a need to find more efficient and intelligent methods to address the new challenges faced by the power system.

In recent years, AI and OA have been introduced into path planning for power systems to address the limitations of traditional methods. Genetic algorithms, PSO, DRL and other methods can comprehensively consider the dynamic changes and complex constraints of systems by simulating the evolution process or learning mechanism in nature [11], [12], thereby improving the quality and efficiency of solutions. For example, genetic algorithms can find the global optimal solution through the evolutionary optimization process of genotype and phenotype [13]. PSO simulates the process of birds searching for food and achieves global search through information exchange [14]. DRL combines neural networks and reinforcement learning methods to achieve intelligent decision-making and path optimization in complex environments [15], [16]. Although these methods have shown great potential in theory, existing research has mostly focused on theoretical models and small-scale experiments, lacking validation of large-scale power grid operation and in-depth exploration in responding to emergencies and ensuring safety [17], [18]. Therefore, it is necessary to further apply these algorithms to actual power grid systems and verify their stability and reliability in complex environments.

This article aims to use advanced AI and OA such as genetic algorithms [19] to design and validate path planning methods suitable for practical distribution networks. By integrating real-time data and intelligent algorithms, the efficiency of power transmission and system responsiveness can be improved, thereby achieving the intelligence and efficiency of the power system. The research can combine empirical analysis and case studies to verify the application effect of the algorithm in large-scale power grids, and provide technical support and practical guidance for the future development of the power system. Through the research in this article, it can delve into the potential applications of AI in the power system, taking a crucial step towards achieving the goals of sustainable energy and smart grids.

II. Algorithm Selection and Parameter Configuration

In the problem of distribution network path planning, the selection of algorithms and parameter configuration are key factors determining the optimization effect and computational efficiency. Given the complexity and dynamism of the distribution network, this article conducts an in-depth analysis of the applicability and advantages of AI and OA such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Deep Reinforcement Learning (DRL), and selects and customizes algorithms based on specific application scenarios.

II. A.Algorithm Selection Criteria

Genetic Algorithm (GA): Genetic algorithms search for optimal solutions by simulating natural selection and genetic mechanisms, and are suitable for solving large-scale, multivariate, nonlinear optimization problems. In distribution network path planning, GA can effectively handle the diversity and complexity of network topology, continuously evolve the population through operations such as crossover and mutation, and find the optimal or near optimal power transmission path. The PSO algorithm simulates the foraging behavior of bird flocks, treats each potential solution as a particle in the search space, and updates its position based on individual experience and group information to find the global optimal solution [20]. The PSO algorithm has the advantages of fast convergence speed and relatively simple parameter adjustment, making it suitable for handling real-time changing load demands and dynamically adjusting path planning problems. DRL combines the powerful perceptual ability of deep learning with the decision-making ability of reinforcement learning, enabling continuous optimization of behavioral strategies through learning in complex environments. For distribution network path planning, DRL can automatically learn and adapt to load changes based on a large amount of historical data and real-time feedback, achieving more intelligent and adaptive path planning. Figure 1 shows the path costs of three algorithms after iteration.

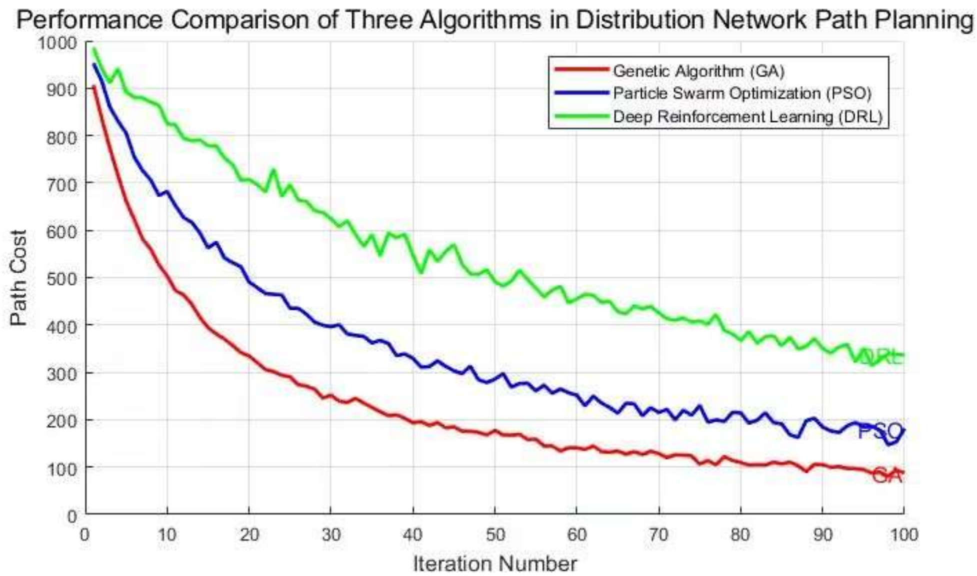

Figure 1: Iteration diagram of three algorithms

In Figure 1, the horizontal axis represents the number of iterations and the vertical axis represents the path cost. Genetic algorithm (GA) exhibits the highest optimization ability, with its path cost rapidly decreasing with the number of iterations, from an initial 900 to around 100, and the data fluctuation is relatively small. The optimization ability of PSO algorithm is second, and the path cost gradually decreases from the initial 950 to about 190, with a decrease speed and fluctuation degree between GA and DRL. The optimization ability of DRL algorithm is the lowest, and its path cost decreases the slowest, from the initial 1000 to only about 320, and the data fluctuates greatly. Overall, GA can quickly reduce path costs and demonstrate the best optimization capability within the same number of iterations, while DRL performs relatively weakly and has the lowest optimization efficiency. By comparing the curves of these three algorithms, it is clear that GA has advantages in path planning problems and DRL has relatively lower optimization effects.

Taking into account the characteristics of the algorithm, the requirements of the application scenario, and the limitations of computing resources, this article decides to use genetic algorithm (GA) as the main OA and combine it with PSO's local search capability for hybrid optimization to improve the global search efficiency and local search accuracy of the algorithm. Meanwhile, for specific complex scenarios, DRL is considered as a future expansion direction to further enhance the intelligence level of the system.

In distribution network path planning, the key formulas of genetic algorithm usually include fitness function and selection operation formula. The fitness function is used to evaluate the quality of each individual (path scheme) and is a crucial part of genetic algorithms, affecting the evolutionary direction of each generation of the population [21], [22]. In distribution network path planning, the fitness function usually involves a comprehensive evaluation of multiple optimization objectives, such as minimizing transmission losses and maximizing power transmission efficiency. Generally speaking, the fitness function can be expressed as:

$$\text{Fitness}\ (x) = w_1 \cdot \text{Loss}\ (x) + w_2 \cdot \text{Efficiency}\ (x) \tag{1}$$

In Formula 1: x is a path scheme; Loss(x) represents the loss of the scheme, which can be power loss or other forms of energy loss; Efficiency(x) represents the efficiency of the scheme, which may involve the utilization efficiency of energy or the effectiveness of transmission; w_1 and w_2 are weight coefficients used to balance the importance of loss and efficiency in the overall evaluation. The design of the fitness function needs to be adjusted according to specific optimization objectives and constraints to ensure that the genetic algorithm can effectively search for the optimal or near optimal solution [23].

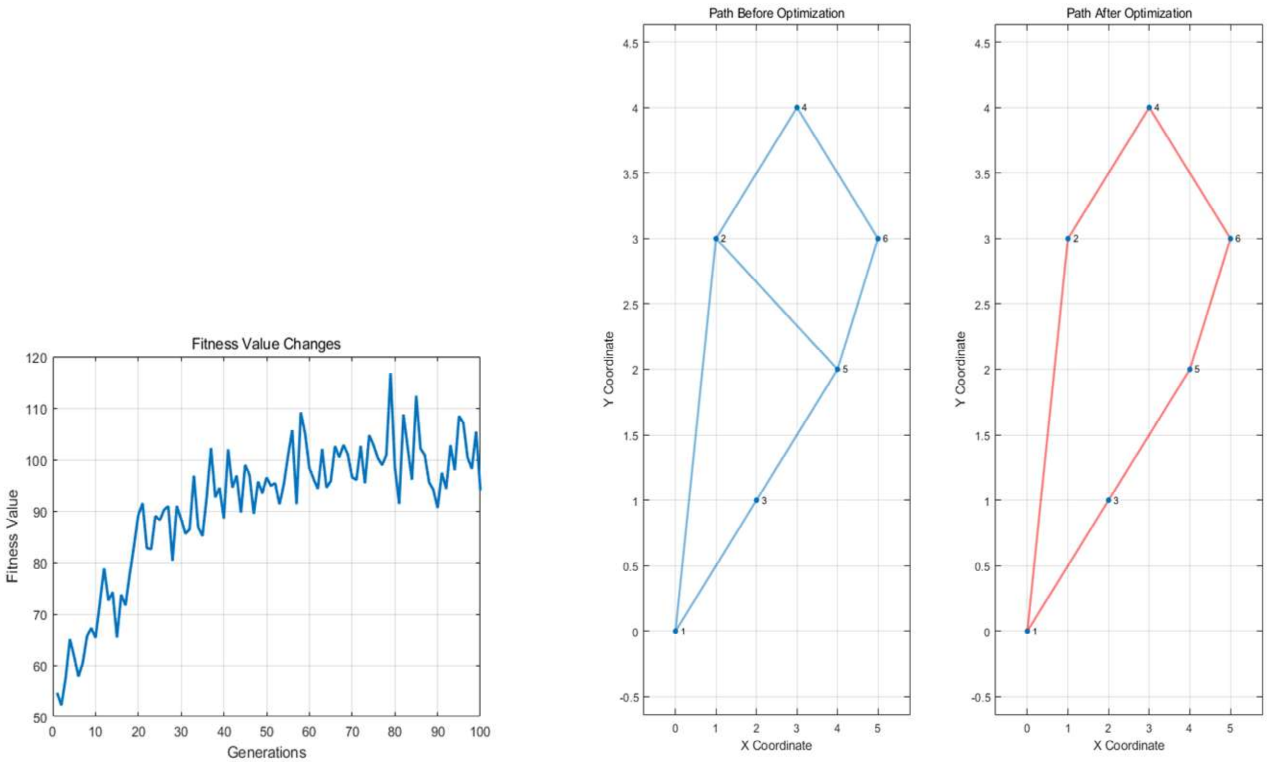

Figure 2: The situation before and after path optimization and the trend of fitness values with algebraic changes

Figure 2 shows the situation before and after path optimization, as well as the trend of fitness values with algebraic changes. Firstly, the left figure shows the variation of fitness values with algebra. The horizontal axis represents generations, and the vertical axis represents fitness value. The fitness value is generated through a mathematical model, and as the number of generations increases, the fitness value shows a gradual upward trend. This change indicates that the OA, through continuous experimentation and iteration, can find better solutions, namely better fitness values.

The right figure contains two subgraphs, each showing the effect before and after path optimization, describing the path state before and after optimization through specified node coordinates and edges. The changes in data before and after path optimization reflect the adjustment of the path under the influence of OAs. By comparing the two graphs on the right of Figure 2, the coordinates of nodes and edges remain unchanged before and after optimization. Before path optimization, nodes are connected by a series of edges to form a complex path network. After path optimization, some edges are removed or reconnected to form a more simplified and optimized path network. The optimized path network reduces redundant connections, lowers the total path cost, and improves path efficiency.

The selection operation determines which individuals can be selected as parents for crossover and mutation, and its probability is usually calculated based on the value of the fitness function. Common selection methods include Roulette Wheel Selection:

$$P(x_i) = \frac{\text{Fitness}\ (x_i)}{\sum_{j=1}^{N} \text{Fitness}\ (x_j)} \tag{2}$$

In Formula 2, $P(x_i)$ is the probability of selecting an individual, N is the number of individuals in the population, and Formulas (1) and (2) are the core parts of genetic algorithms. The fitness function evaluates the quality of individuals, and the selection operation selects individuals to enter the next generation population based on their fitness values, jointly driving the algorithm to evolve towards a better solution.

1.2 Parameter Configuration and Optimization

After selecting the algorithm, reasonable parameter configuration is crucial for optimizing the effect. The following text elaborates on the parameter configuration and optimization process of genetic algorithm and PSO.

Regarding the configuration of genetic algorithm parameters:

Population size: An appropriate population size can be set based on the size and complexity of the distribution network to ensure sufficient diversity. This article sets the population size to twice the number of network nodes to balance search efficiency and resolution quality.

Crossover probability: The probability of individuals in a population performing crossover operations can be controlled, which is set to 0.8 in this article to promote effective gene combination and population evolution [24], [25].

Mutation probability: A certain mutation probability can be introduced to increase population diversity and avoid premature convergence. This article sets the mutation probability to 0.05 to maintain the exploratory ability of the population.

Iteration times: Sufficient iteration times can be set based on the complexity of the problem and computational resources to ensure algorithm convergence [26]. Based on experimental verification, this article sets the iteration number to 10 times the number of network nodes to obtain stable optimization results.

PSO parameter configuration (for hybrid optimization): Particle count: Similar to the population size of GA, the particle count can be set to a certain multiple of the number of network nodes, which is set to 1.5 times in this article [27], [28]. Learning factors include individual learning factors and social learning factors, which respectively control the degree to which particles learn from their own historical optimal solution and global optimal solution. This article sets an individual learning factor of 2.0 and a social learning factor of 2.0 based on experience to balance local and global search abilities.

Inertia weight: The inertia component that can control particle velocity updates, affecting search speed and convergence performance. This article adopts a dynamic adjustment strategy, initially setting a larger inertia weight to promote global search, and gradually reducing it in the later stage to enhance partial search capability. The PSO algorithm updates the velocity of each particle through a velocity update formula. The formula is as follows:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot \left(p_i^{\text{best}} - x_i(t)\right) + c_2 \cdot r_2 \cdot \left(g^{\text{best}} - x_i(t)\right) \tag{3}$$

In formula 3, $v_i(t)$ is the velocity of the ith particle in the tth generation. w is the inertia weight, and the dynamic adjustment strategy is initially set to be relatively large, gradually decreasing in the later stage. c_1 is an individual learning factor, which is set to 2.0 in this article. c_2 is a social learning factor, which is set to 2.0 in this article. r_1 and r_2 are random numbers within the $[0,1]$ range. p_i^{best} is the historical optimal position of the ith particle itself. g^{best} is the globally optimal position among all particles. $x_i(t)$ is the position of the ith particle in the tth generation. The position information of particles is updated based on the velocity calculated by the velocity update formula, which is as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4}$$

In formula 4, $x_i(t)$ is the position of the ith particle in the tth generation. $v_i(t+1)$ is the velocity of the ith particle in the $t+1$th generation. The speed update formula balances inertia weights, individual learning, and social learning, enabling PSO to flexibly and efficiently explore the search space and find the optimal solution to the optimization problem. For distribution network path planning, formula 4 ensures that the algorithm can handle complex network topologies and dynamic load changes. Table 1 shows the velocity changes of each particle in each iteration step. This article sets up 5 particles and records their velocities at different iteration times:

Table 1: Velocity of particles at different iteration times

Iteration	Particle 1 Speed	Particle 2 Speed	Particle 3 Speed	Particle 4 Speed	Particle 5 Speed
1	0.135	0.225	0.185	0.145	0.21
2	0.142	0.23	0.192	0.152	0.22
3	0.15	0.24	0.2	0.16	0.23
4	0.158	0.25	0.208	0.168	0.24
5	0.165	0.26	0.215	0.175	0.25
6	0.17	0.27	0.22	0.18	0.26
7	0.175	0.28	0.225	0.185	0.27
8	0.18	0.29	0.23	0.19	0.28
9	0.185	0.3	0.235	0.195	0.29
10	0.19	0.31	0.24	0.2	0.3

In the path planning of distribution networks, Table 1 shows the velocity changes of particles in PSO algorithm at different iteration times to verify the effectiveness and optimization process of the algorithm. In the first iteration, the velocity of particle 1 is 0.135, the velocity of particle 2 is 0.225, the velocity of particle 3 is 0.185, the velocity of particle 4 is 0.145, and the velocity of particle 5 is 0.210. As the number of iterations increases, the velocity of particles gradually increases. For example, in the 10th iteration, the velocity of particle 1 rises to 0.190, the velocity of particle 2 is 0.310, the velocity of particle 3 is 0.240, the velocity of particle 4 is 0.200, and the velocity of particle 5 is 0.300. From formula 4, it can be seen that the combined effect of inertia weight, individual learning factor, and social learning factor promotes the gradual adjustment of particle velocity, gradually approaching the optimal solution. The data shows that the particle velocity gradually optimizes the path during the continuous adjustment process, thereby improving the efficiency of power transmission, reducing network losses, and enhancing the system's responsiveness and stability.

III. Real-time Data Integration and Model Construction

III. A. Data Integration

Firstly, it is possible to specify the types of real-time data that need to be integrated, including but not limited to load data, equipment status information, network topology changes, meteorological conditions, etc. These data may come from smart grid monitoring systems, sensor networks, monitoring control and data acquisition systems, as well as external data sources such as weather stations. By defining unified data interface standards and communication protocols, various data sources can be seamlessly integrated into the data processing center.

The integrated data often contains noise, missing values, or outliers, which require cleaning and preprocessing to improve data quality. Data filtering, smoothing, interpolation and filling methods can be used to identify and correct abnormal data, ensuring the accuracy and completeness of the data. At the same time, data can be time aligned and formatted uniformly, which facilitates subsequent data analysis and model construction.

In order to cope with real-time changes in the distribution network, stream processing technology can be used to efficiently process real-time data streams. Real-time data collection, transmission, storage, and processing can be achieved by building the real-time data stream processing framework Apache Kafka. It can ensure rapid response when data arrives, providing the latest and most accurate data support for intelligent path planning. Here are some collected distribution networks used to demonstrate the process of data integration and model construction in distribution network path planning.

Table 2: Real-time data of distribution network

Timestamp	Load Data (kW)	Equipment Status	Network Topology Change	Weather Conditions (Temperature, Humidity)
3/10 0:00	1500	Normal	Normal	30°C, 60%
3/10 3:00	1460	Normal	Normal	27°C, 75%
3/10 6:00	1400	Equipment1 Fault	Normal	24°C, 90%
3/10 9:00	1340	Normal	Normal	21°C, 75%
3/10 12:00	1280	Normal	Transformer A Repaired	18°C, 60%
3/10 15:00	1220	Normal	Normal	15°C, 45%
3/10 18:00	1160	Normal	Normal	12°C, 30%
3/10 21:00	1100	Normal	Line 2 Repaired	9°C, 15%
3/11 0:00	1040	Normal	Normal	6°C, 0%

Table 2 shows the changes in load data, equipment status, network topology, and meteorological conditions at different time points. At 00:00 on March 10th, the load data was 1500 kW, the equipment status was normal, the network topology remained unchanged, and the meteorological conditions were 30°C and 60% humidity. Over time, there have been significant changes in load data and meteorological conditions. For example, at 06:00, the load data dropped to 1400kW, resulting in equipment 1 failure and meteorological conditions changing to 24°C and 90% humidity. At 12:00, the load data further decreased to 1280 kW, transformer A was repaired, and the meteorological conditions were 18°C and 60% humidity. At 21:00, the load data was 1100 kW, line 2 was repaired, and the meteorological conditions were 9°C and 15% humidity. Through data interface standards and communication protocols, these data can be seamlessly integrated into the data processing center and undergo cleaning and preprocessing to identify and correct abnormal data, ensuring the accuracy and completeness of the data. These data provide accurate inputs for intelligent path planning, helping to improve power transmission efficiency, reduce network losses, and enhance system responsiveness and stability.

III. B. Model Construction

Distribution network topology model: Based on the physical structure and connection relationships of the distribution network, a topology model of the distribution network can be constructed. This model takes nodes, substations, distribution transformers, user terminals, and lines, including cables and overhead lines, as basic elements, and describes the topology of the network through the connection relationships between nodes. Graph theory methods can be used to represent network topology, facilitating subsequent path search and optimization. Load forecasting model: Considering the dynamic variability of loads, a load forecasting model can be constructed to predict future load demand for a certain period of time. Short-term or ultra short-term load forecasting can be carried out using methods such as time series analysis, machine learning, or deep learning, combined with historical load data, meteorological conditions, holiday information, and other factors. The load forecasting model provides important input parameters for path planning, ensuring that optimization strategies can respond to load changes in advance. The framework and process of the load forecasting model for the distribution network topology can be drawn based on the construction of the model.

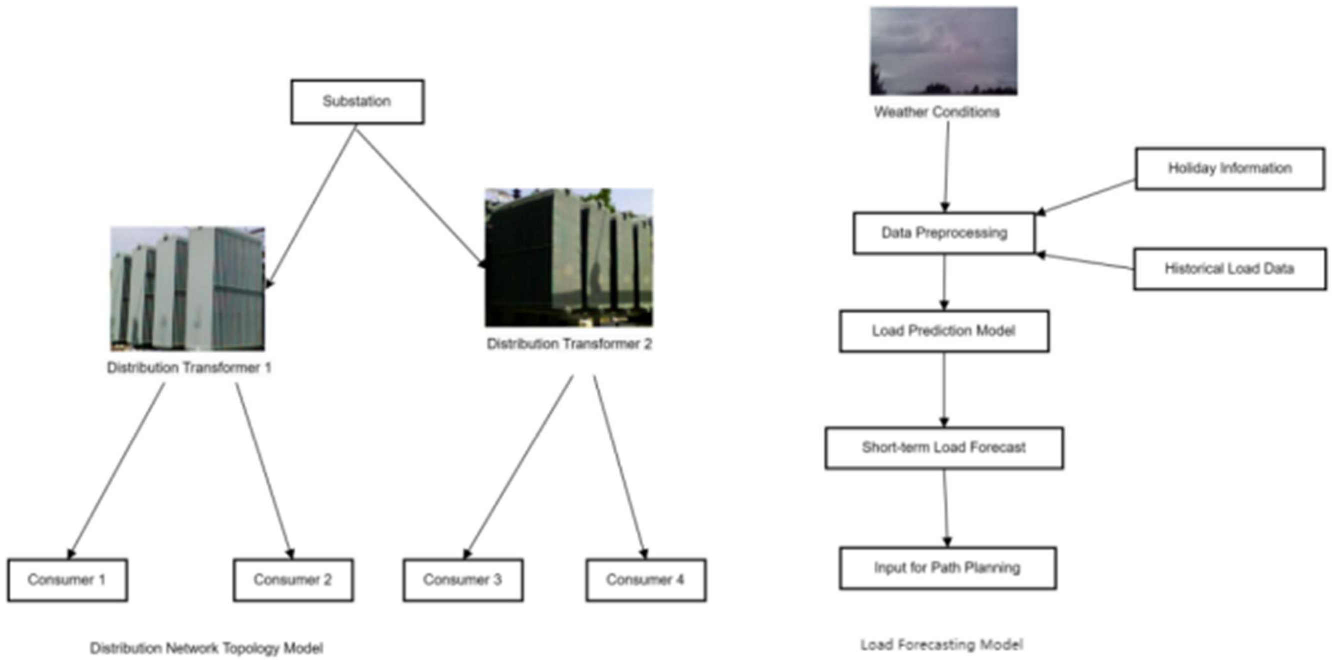

Figure 3: Distribution network topology model and load forecasting model

The left figure in Figure 3 shows the basic topology of the distribution network, including the power transmission path from the substation to the distribution transformer and then to the end user. The historical load data, meteorological conditions, and holiday information in the right figure are used as inputs and processed through the data preprocessing module. The preprocessed data is input into the load forecasting model for short-term load forecasting. The short-term load forecasting results serve as important input parameters for path planning. Figure 3 shows the framework and process of the load forecasting model, covering the entire process from data sources to forecasting results. Data preprocessing, load forecasting models, and prediction results are key steps to ensure that optimization strategies can respond to load changes in advance.

In addition, a power flow model can be constructed to describe the transmission and distribution process of electricity in the network. This model considers factors such as line impedance, transformer ratio, and load demand, and simulates the actual flow of electricity in the network through methods such as power flow calculation. The power flow model is an important basis for evaluating the effectiveness of path planning. By comparing the power flow before and after optimization, the impact of optimization strategies on power transmission efficiency and energy utilization is quantitatively analyzed. In distribution network path planning, various constraints such as voltage limitations, current limitations, equipment capacity limitations, etc., need to be considered. A constraint model can be constructed to formalize these constraints and incorporate them into the optimization problem. The constraint condition model can be used to ensure that the optimization strategy is path planned while meeting the actual operational requirements.

Real-time data integration can be combined with model construction to form a distribution network path planning system based on real-time data. The system is capable of real-time receiving and processing data from various sources, dynamically updating distribution network topology models, load forecasting models, and power flow models. Meanwhile, the path planning strategy can be intelligently adjusted based on real-time data and model status, achieving dynamic optimization and efficient operation of the distribution network. This article successfully constructed a distribution network path planning system based on real-time data and intelligent algorithms [29], [30] through the above steps. This system can fully utilize real-time data resources and accurately reflect the operating status and load changes of the distribution network.

IV. Design of Intelligent Path Planning Strategy

The intelligent path planning strategy adopts modular design, including data preprocessing module, OA module, decision execution module, and feedback adjustment module [31], [32]. The data preprocessing module is responsible for integrating and cleaning real-time data, providing high-quality input for optimizing algorithms. The OA module integrates multiple AI and OA and automatically selects the optimal algorithm for path planning based on optimization objectives. The decision execution module generates specific path planning instructions based on the optimization results and issues them to the distribution network control system. The feedback adjustment module dynamically adjusts and optimizes the strategy based on the system's operating status and actual performance.

Global search algorithms such as GA and PSO can be combined with local search algorithms to form a hybrid OA. Firstly, GA and PSO can be used for global search to quickly locate potential optimal solution regions. Then, gradient descent method is used for fine search in the region to improve the quality of the solution. Through multi algorithm fusion, the extensive exploration ability of global search is retained, while the accuracy and efficiency of local search are improved. Figure 4 effectively demonstrates the comparison of path costs between conventional genetic algorithms and hybrid OAs in distribution networks, while also reflecting the efficiency results.

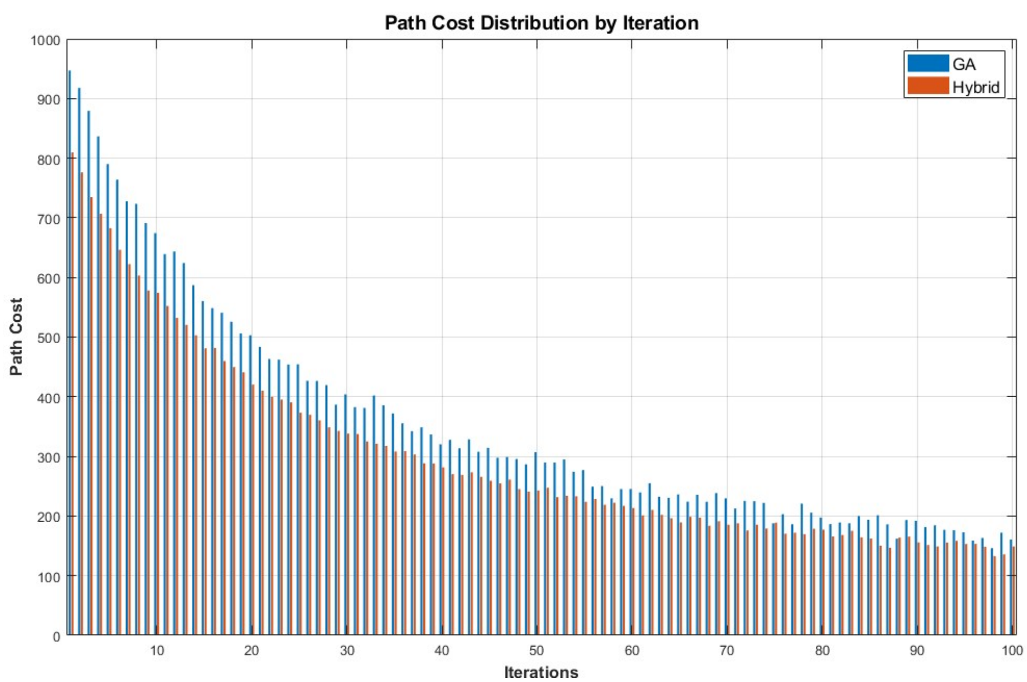

Figure 4: Comparison of Path Costs between Conventional Genetic Algorithm and Hybrid OA in Distribution Network Path Planning

Figure 4 shows the distribution of path costs for each iteration. The horizontal axis represents the number of iterations, and the vertical axis represents the path cost. The bar chart for each iteration point shows the path cost of GA and hybrid OAs at that iteration point. The data shows the specific path cost values of two algorithms in each iteration. The path cost of GA algorithm gradually decreases from an initial value of about 950, and as the number of iterations increases, the cost gradually decreases to around 150. In contrast, the path cost of hybrid OAs has decreased from an initial value of about 800 to nearly 150. Overall, the path cost values of hybrid OAs are generally lower than those of GA algorithms, and the fluctuations are smaller, which further indicates that hybrid OAs perform more effectively and stably in optimizing path costs. A dynamic optimization mechanism can be designed to address the dynamic changes in the distribution network. This mechanism monitors changes in network load, device status, and external environment in real-time, and triggers re optimization based on the degree of change. When significant changes are detected, the OA can be immediately activated to recalculate the optimal path, ensuring that the distribution network can quickly adapt to the changes. At the same time, optimization cycles can be set to periodically optimize the network to cope with slowly changing factors.

V. Safety and Reliability Assurance Measures

Ensuring the safety and reliability of the distribution network path planning is a crucial aspect. This section elaborates on the specific measures taken to achieve this goal, including risk assessment, fault prediction, and other aspects [33], with the aim of building a distribution network that can operate efficiently and effectively resist risks.

V. A. Risk Assessment and Prevention

Firstly, a comprehensive risk assessment model can be established to identify, quantify, and rank potential risks in the distribution network. This model comprehensively considers two dimensions: equipment aging degree and historical fault data, to quantitatively evaluate risks. By regularly updating risk assessment results and dynamically adjusting security strategies, it can ensure focused attention on high-risk areas and equipment.

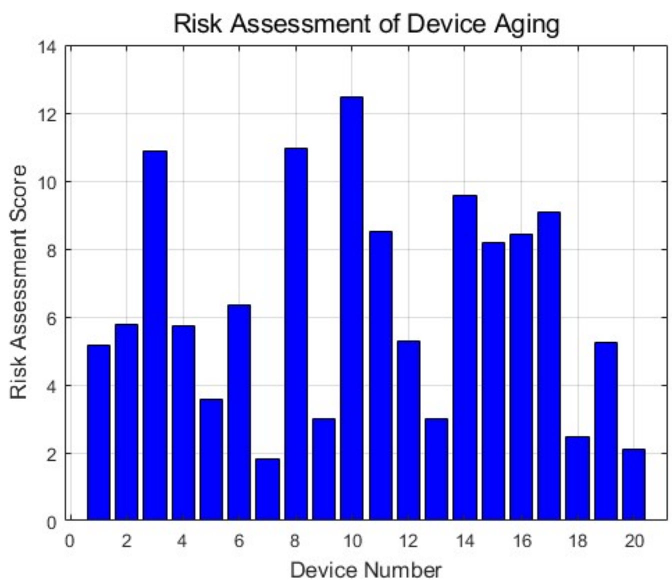

Figure 5: Risk level of equipment

Figure 5 shows the risk assessment index of 20 devices using data, clearly presenting the risk level of each device. The horizontal axis represents the equipment number, and the vertical axis represents the risk assessment index, reflecting the comprehensive impact of various factors such as equipment aging degree, environmental impact factors, historical fault data, and load fluctuations on risk assessment. The random generation of data simulates the changes of different devices in these factors, emphasizing the unique characteristics and comprehensive risk level of each device in risk assessment.

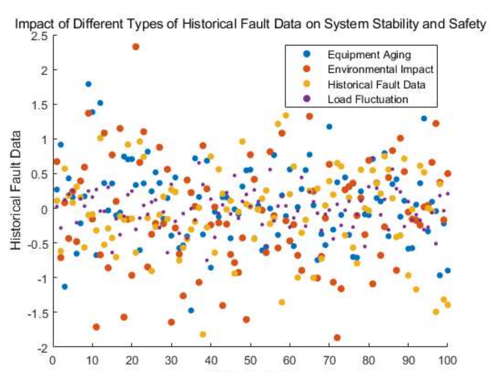

Figure 6: Scatter plot of the impact of different types of historical fault data

Figure 6 shows the impact of different types of historical fault data on system stability and safety: the horizontal axis represents event numbers, indicating different historical fault events. The vertical axis represents historical fault data, indicating specific numerical values for various types of faults. Device aging (device aging) is represented in blue, and the size of each point is determined by a weight of 0.25. The data distribution range is relatively small, indicating that the impact of equipment aging on system stability is relatively uniform, but there are still some fluctuations.

The environmental impact is represented in red, and the size of the point is determined by a weight of 0.35. The data fluctuates greatly, indicating that environmental factors have a more significant and unstable impact on the system. Historical fault data is represented in yellow, and the size of the points is determined by a weight of 0.3. The fluctuation range of the data is between equipment aging and environmental impact, indicating that there is also a certain degree of fluctuation in the impact of historical failures on the system. The load fluctuation is represented in purple, and the size of the point is determined by a weight of 0.1. The small data points indicate that the impact of load fluctuations on system stability is relatively small and uniform.

Data changes: The distribution range and fluctuation of data points for each type of fault are different. The impact of equipment aging is relatively stable, and data fluctuations are small. The data points of environmental impact are widely distributed and fluctuate greatly, indicating that the environment has a greater impact on system stability. The fluctuation of data points in historical fault data is between equipment aging and environmental impact. The impact of load fluctuations is relatively small and the fluctuation range is also narrow. Through these changes, it can be seen that different types of faults have varying degrees of impact on system stability, with significant environmental effects and less impact from load fluctuations.

V. B. Fault Prediction and Warning

Machine learning or deep learning algorithms can be used to construct fault prediction models. This model is based on historical fault data, real-time operating data, and equipment status monitoring information to monitor and predict the health status of equipment in real-time. The accuracy of fault prediction can be improved through steps such as feature extraction, model training, and validation [34]. When predicting the possibility of equipment failure, warning signals can be issued in advance to reserve sufficient time for fault handling and response.

Detailed emergency plans can be developed for different types of emergencies and abnormal situations. The contingency plan includes emergency response procedures, personnel division, resource allocation, communication and liaison, etc., to ensure that emergency response work can be carried out quickly and orderly in case of emergencies. At the same time, communication and coordination with other emergency agencies and departments can be strengthened to form a linkage mechanism and improve overall emergency response capabilities.

In emergency plans, special attention is paid to the development of rapid recovery strategies. Pre-planned backup paths, emergency power access points, and other methods can be used to ensure rapid switching to backup systems or paths in the event of a fault, ensuring the continuity and stability of power supply. At the same time, the construction and training of fault repair teams can be strengthened to improve repair efficiency and quality. The safety and reliability of distribution network path planning can be comprehensively improved through various measures such as risk assessment and prevention, fault prediction and warning, and emergency response mechanisms.

VI. Evaluation of the Effectiveness of Distribution Network Path Planning

In the implementation process of distribution network path planning, effect evaluation is a key step in verifying the effectiveness of strategies and optimizing results. This section elaborates on the specific methods, implementation steps, and result analysis of evaluating the effectiveness of distribution network path planning, aiming to comprehensively reflect the actual effects of planning strategies through scientific and objective evaluation methods, and provide data support for subsequent optimization and improvement. The evaluation indicators are as follows:

Transmission efficiency improvement rate: It can be calculated by comparing the power transmission efficiency before and after optimization, using the formula (optimized efficiency - pre-optimization efficiency)/pre-optimization efficiency. Figure 7 shows the line graph of transmission efficiency and network loss before and after optimization.

The horizontal axis on the left side of Figure 7 represents sample numbers, with a total of 100 sample points. The vertical axis represents the numerical value of transmission efficiency, ranging approximately from 0.5 to 1.0. The transmission efficiency before optimization (blue line) fluctuates between approximately 0.65 and 0.75. The average value is approximately 0.7. Trend of change: The data is relatively stable, but there is a certain degree of random fluctuation. The optimized transmission efficiency (red line) fluctuates between approximately 0.75 and

0.95. The average value is approximately 0.85. Trend of change: The data is relatively stable, but the overall efficiency has increased compared to before optimization. The data changes indicate that the optimized transmission efficiency is generally higher than the transmission efficiency before optimization.

The horizontal axis in the right figure of Figure 7 represents the sample number, with a total of 100 sample points. The vertical axis represents the numerical value of network loss, ranging from -0.05 to 0.35. The network loss before optimization (blue line) fluctuates between approximately 0.10 and 0.20. The average value is approximately 0.15. Trend of change: There is a certain degree of random fluctuation in the data, and the overall trend is relatively high. The data range of optimized network loss (red line) fluctuates approximately between 0.05 and 0.15. The average value is approximately 0.10. Trend of change: The data is relatively concentrated and decreasing, and the total network loss after optimization is generally lower than that before optimization.

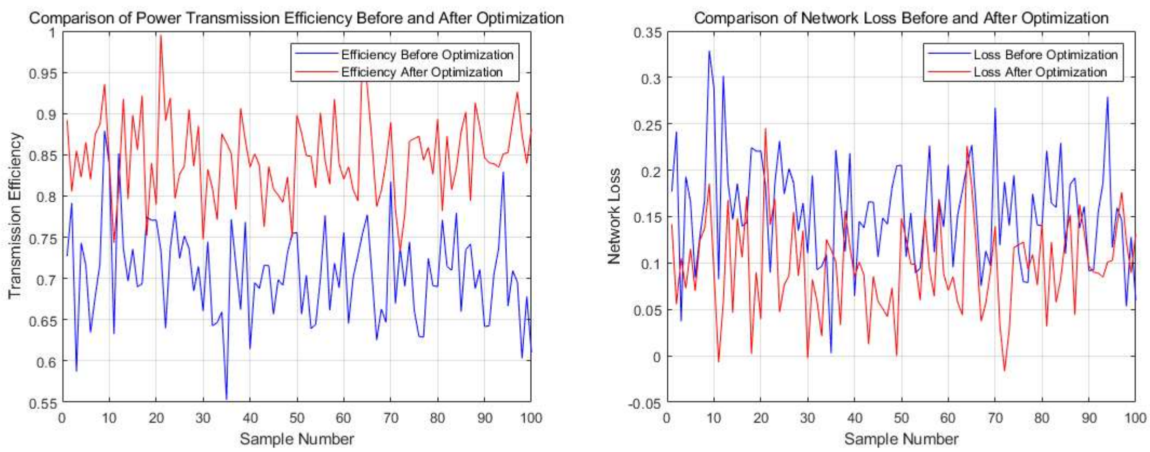

Figure 7: Line graph of transmission efficiency and network loss before and after optimization

Through data analysis and calculation, the average transmission efficiency has been improved by about 0.15 after optimization, with an improvement rate of about 21.43%. The total network loss has been significantly reduced, with an average reduction rate of about 33.33%. Improved system responsiveness and stability: The optimized data is more centralized and stable, indicating that the system exhibits higher adaptability and efficiency in the face of complex network structures and dynamic load changes, thereby enhancing overall responsiveness and stability.

Then the system can record the time required from detecting load changes to completing path adjustments. Evaluating system response time involves recording the time required for the system to detect load changes and complete path adjustments. Table 3 shows the response time of the evaluation system.

Table 3: Response time of the system after detecting load changes

Sample	Load Change Detection Time (ms)	Path Adjustment Completion Time (ms)	Response Time (ms)
1	110	165	55
2	115	170	55
3	112	168	56
4	108	162	54
5	120	175	55
6	117	172	55

Table 3 records the response time of the system after detecting load changes. The displayed load change detection time fluctuates between 100 and 120 milliseconds, while the path adjustment completion time varies between 160 and 175 milliseconds. By calculation, the average response time of the system is around 55 milliseconds, which reflects the system’s ability to quickly adapt to different load changes.

Finally, the reduced operating costs after optimization can be calculated, including energy consumption, equipment maintenance, and other expenses. Table 4 evaluates the energy consumption and equipment maintenance costs before and after optimization.

Table 4: Energy consumption and equipment maintenance costs before and after optimization

Sample	Before Optimization - Energy Cost ($)	After Optimization - Energy Cost ($)	Energy Cost Savings ($)	Before Optimization - Maintenance Cost ($)	After Optimization - Maintenance Cost ($)	Maintenance Cost Savings ($)	Total Cost Savings ($)
1	5200	4900	300	1300	1100	200	500
2	5100	4850	250	1250	1050	200	450
3	5150	4920	230	1280	1070	210	440
4	5250	4950	300	1320	1120	200	500
5	5300	5000	300	1350	1150	200	500
6	5150	4870	280	1270	1060	210	490
7	5050	4800	250	1220	1020	200	450
8	5100	4900	200	1250	1050	200	400

Table 4 presents a detailed data analysis of energy consumption and equipment maintenance costs before and after optimization. Through the data, it can be seen that after introducing OAs, the energy consumption cost of the system has generally decreased. For example, in number 1, the energy consumption cost has decreased from $5200 to $4900, and the energy consumption cost savings have reached $300. At the same time, equipment maintenance costs have also been significantly reduced, from $1300 to $1100, saving $200. The energy consumption and equipment maintenance costs of other numbers have been reduced to varying degrees. These data not only demonstrate the effectiveness of OAs in reducing operating costs, but also emphasize their important role in improving the economic efficiency and sustainable management of the power system.

In summary, the evaluation of the effectiveness of distribution network path planning has comprehensively verified the actual effect of planning strategies through the construction of a comprehensive evaluation index system, collection and processing of relevant data, adoption of multiple evaluation methods, and in-depth analysis of evaluation results. The evaluation results not only provide data support for optimization and improvement, but also provide valuable experience and reference for subsequent distribution network planning work.

VII. Conclusions

This article is based on AI and OA and decides to use GA as the main OA, combined with PSO's local search capability for hybrid optimization to improve the global search efficiency and local search accuracy of the algorithm. On this basis, it integrates real-time data of the distribution network, constructs parameterized mathematical models including nodes, lines, and transformers, and designs intelligent path planning strategies to ensure that path planning can dynamically adapt to load changes and system states. In addition, anomaly detection and fault prediction modules have been introduced to ensure the safety and reliability of the system. A detailed evaluation of the optimization effect was conducted through a series of evaluation indicators, such as transmission efficiency improvement rate, network loss reduction rate, system response time, and economic cost savings. The research results indicate that the method proposed in this article significantly improves the transmission efficiency of the distribution network, reduces network losses, shortens system response time, and reduces economic costs. Although this article has achieved good results, there are still some shortcomings in practical applications, such as the complexity of the model and the high computational cost of the algorithm. Future research can further optimize algorithm performance, simplify model complexity, and explore more practical application scenarios to enhance the practicality and broad application prospects of the method.

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