Topology Planning and Optimization of DC Distribution Network Based on Mixed Integer Programming and Genetic Algorithm

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***Abstract*—In the current situation of rapid development of the power industry, DC distribution network topology planning and optimization are of vital importance. This research studies the shortcomings of existing methods in terms of computational efficiency and optimization effect. Based on the real data of a medium-sized DC distribution network in a large city with 200 nodes and 350 lines, an innovative method combining mixed integer programming (MIP) and genetic algorithm (GA) is adopted. MIP is used to accurately describe physical constraints and optimization objectives, and GA efficiently searches for the best solution in the solution space with its global search capability. Experimental results show that the MIP-GA model has the lowest power transmission loss at different load levels. For example, at high load, it is 32% lower than the baseline, 16% lower than the MIP model, and 12.5% lower than the ACO model. It also performs best in terms of node voltage deviation, reliability, power quality and other indicators. Cost-benefit analysis shows that although the MIP-GA model has a relatively high investment cost for topology adjustment, it has the lowest annual power loss and maintenance cost, a reasonable total annual cost, a benefit-cost ratio of 1.5, and a payback period of only 3 years. Research has shown that this hybrid model has significant advantages in DC distribution network topology planning and optimization, and can effectively improve system performance and economic benefits.**

Keywords*—*DC distribution network; topology planning; mixed integer programming; genetic algorithm; optimization effect

I. Introduction

In the current rapid development of the power industry, the planning and optimization of distribution networks has become an extremely critical and complex issue, especially in the field of DC distribution networks. According to incomplete statistics, more than 30% of power-related companies worldwide have been involved in DC distribution network-related businesses to varying degrees, and its market size is expected to increase at an annual rate of about 15% in the next five years [1]. However, in the actual operation and development of DC distribution networks, their topology planning and optimization have always been severely restricted by many factors. For example, in the power supply system of a large city, the DC distribution network has an unreasonable topology structure, resulting in a power transmission loss of about 20%. This not only causes huge energy waste, but also greatly reduces the stability of power supply. During peak power consumption periods, the probability of power outages caused by improper topology planning is about 35% higher than that of a reasonably planned distribution network [2]. In addition, in some emerging industrial parks, due to the lack of effective topology optimization strategies, the average electricity cost of enterprises has increased by about 25%, seriously affecting the economic benefits of enterprises and the overall development of the park. These phenomena fully demonstrate the importance and urgency of DC distribution network topology planning and optimization. It is no longer just a simple technical issue, but a major issue related to energy efficiency, power supply stability, and the economic development of many enterprises and regions. It urgently needs to be solved in a more in-depth and effective way [3].

In the current academic field, research on DC distribution network topology planning and optimization has achieved certain results. Many scholars have used various methods to conduct relevant explorations. Among them, a considerable number of studies focus on traditional mathematical programming methods, such as linear programming, and try to solve topology planning problems by establishing a series of mathematical models. For example, a well-known research team used linear programming methods to plan the topology of a small DC distribution network [4], which reduced the transmission loss by about 10% to a certain extent. However, this method is often limited by the complexity of the model and the efficiency of calculation, and is less applicable to large-scale DC distribution networks. At the same time, many studies have introduced intelligent algorithms, such as ant colony algorithms. Studies have shown that in certain specific DC distribution network scenarios, the use of ant colony algorithms can optimize the topology structure to a certain extent, thereby improving the reliability of the network by about 12%. However, this type of algorithm also has its own defects, such as being prone to falling into local optimal solutions, and the parameter settings in the calculation process are relatively complex and lack a unified standard [5]. It can be seen that although the current research has achieved results, it still has obvious shortcomings. Hot issues mainly focus on how to balance the contradiction between computational efficiency and planning optimization effect, and how to improve the versatility of algorithms in DC distribution networks of different scales and complexities. The controversial point is whether the improvement of traditional mathematical programming methods has more potential or the improvement of emerging intelligent algorithms can more

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effectively solve the problem. The opinions of all parties are different and lack convincing evidence.

This research aims to conduct an in-depth study on the topology planning and optimization of DC distribution networks based on mixed integer programming and genetic algorithms. The key lies in solving the problems of the existing methods in terms of imbalance in computational efficiency and optimization effect, as well as the lack of versatility. Its innovation lies in the integration of the advantages of the two algorithms, which is expected to greatly improve the effect of topology planning and optimization. It has a significant potential impact both in theoretically improving the relevant algorithm system and in practice improving the operating efficiency of DC distribution networks [6].

The remainder of the research is organized as follows: Section II reviews related works on traditional mathematical programming and intelligent algorithms in the context of DC distribution network topology planning and optimization. Section III introduces the research methodology, including the fundamentals of mixed integer programming, genetic algorithm adaptation, and the proposed hybrid model. It compares the proposed model with conventional methods and analyzes its advantages in terms of accuracy, stability, and computational efficiency. Section IV presents the experimental setup and results based on a real-world dataset, including performance evaluation under various conditions such as load variation, distributed generation, and fault scenarios. The research concludes with a summary of key findings and insights into practical implications and future directions in the field of DC distribution network optimization in Section V.

II. Literature Review

A. Analysis of Traditional Methods Related to DC Distribution Network Topology Planning and Optimization

Traditional mathematical programming methods have been widely used in DC distribution network topology planning and optimization, among which linear programming methods have attracted the attention of many researchers. Research data shows that in some small-scale DC distribution network scenarios, the power transmission loss can be reduced by about 10% after the linear programming method is applied. This achievement is remarkable. However, its disadvantages are also very obvious. The two problems of model complexity and computational efficiency have always restricted it. When facing a large-scale DC distribution network, its model construction will become extremely complex, the time required for calculation will increase significantly, and the efficiency will be seriously reduced, resulting in a significant reduction in its applicability. Moreover, the model established by the linear programming method is often based on some idealized assumptions [7], which is somewhat different from the complex situation in the actual operation of the DC distribution network, which makes its optimization effect greatly reduced in actual application and cannot meet the actual needs well. In addition to linear programming, other traditional mathematical programming methods such as integer programming also have similar problems. Although integer programming can more accurately describe the discrete characteristics of the DC distribution network topology in theory, in the actual calculation process, due to the large number of variables and constraints, the amount of calculation will increase exponentially, resulting in extremely low calculation efficiency and often unable to obtain an effective solution within an acceptable time. Although these traditional mathematical programming methods have made certain contributions to the DC distribution network topology planning and optimization, they are difficult to achieve breakthrough progress due to their own limitations and are gradually being impacted by some new methods in current research [8].

B. Application and Defects of Intelligent Algorithms in DC Distribution Network Topology Planning and Optimization

Intelligent algorithms have gradually emerged and attracted attention in the field of DC distribution network topology planning and optimization. Taking the ant colony algorithm as an example, relevant experimental data shows that the application of the ant colony algorithm in a specific DC distribution network scenario can improve network reliability by about 12%, which shows its certain advantages in optimizing topology structures. However, the defects of the ant colony algorithm itself cannot be ignored. It is very easy to fall into the local optimal solution during the calculation process, and thus cannot obtain the global optimal topology structure. In addition, its parameter setting is relatively complex and lacks a unified standard. Different parameter settings will lead to large differences in optimization results, which makes it difficult to accurately grasp its optimal parameter combination in practical applications, thereby affecting the stability of its optimization effect [9]. Similarly, genetic algorithm, as another commonly used intelligent algorithm, has also been applied to DC distribution network topology planning and optimization. Genetic algorithm has certain advantages in dealing with complex nonlinear problems and can search for better topology structures to a certain extent. However, it also has problems such as high computational complexity and slow convergence speed. Especially in large-scale DC distribution networks, its calculation time may become very long, and its initial population setting will also have a great impact on the final result. If the initial population setting is unreasonable, it may cause the optimization result to deviate from the ideal state. Its versatility and stability still need to be improved [10].

C. Comprehensive Evaluation

In general, both traditional mathematical programming methods and intelligent algorithms have their own advantages and disadvantages in DC distribution network topology planning and optimization. Although traditional methods have a theoretical basis, they are limited by computational efficiency and model limitations in practical applications; although intelligent algorithms have certain optimization capabilities, they have many defects such as easy to fall into local optimality and complex parameter settings. The current research status shows that a general method that can perfectly solve the DC distribution network topology planning and optimization problem has not yet been formed in this field. The future research direction should be to integrate the advantages of multiple methods and make up for their respective shortcomings. For example, we can try to combine the precise modeling ability of traditional mathematical programming methods with the global search ability of intelligent algorithms to construct a more universal and efficient hybrid algorithm. At the same time, in the optimization process of the algorithm, the actual operating characteristics of the DC distribution network, such as the dynamic changes of loads and the access of distributed power sources, should be fully considered, so that the algorithm can be more in line with the actual situation, thereby improving its effectiveness and stability in practical applications. In addition, the algorithm evaluation system should be further improved. It should not be limited to single indicators such as transmission loss and network reliability, but should take into account multiple factors to more comprehensively evaluate the advantages and disadvantages of the algorithm and promote the further development of DC distribution network topology planning and optimization research [11, 12].

While existing approaches such as traditional mathematical programming and intelligent algorithms have achieved some progress in DC distribution network topology planning, they still face distinct limitations. Traditional methods like linear and integer programming suffer from computational inefficiency and scalability issues when applied to large-scale networks. On the other hand, intelligent algorithms such as ACO and GA are prone to local optima and unstable performance due to sensitive parameter settings. These drawbacks highlight a critical gap in achieving both accuracy and efficiency under real-world constraints. The proposed hybrid approach integrates the modeling precision of mixed integer programming with the global search capability of genetic algorithms, thereby addressing this dual challenge. Unlike prior studies, the new method demonstrates significantly reduced power losses (e.g., 32% lower than baseline at high load) and faster convergence (average 600 iterations versus 1000 in MIP), while maintaining robust adaptability to load and generation fluctuations.

III. Research Methods

A. Mixed Integer Programming Basics

In the complex and critical research field of DC distribution network topology planning and optimization, Mixed-Integer Programming (MIP) is undoubtedly an important cornerstone for building the core model framework. MIP's ability to handle optimization problems involving integer variables and continuous variables is highly consistent with the topological structure and operating characteristics of DC distribution networks. In a DC distribution network, the line connection state is typically discrete and can be accurately described by binary variables, while physical quantities such as power flow and voltage belong to the category of continuous variables.

Assume that the DC distribution network consists of n nodes and m lines. In order to accurately characterize the line connection status, a binary variable is defined x_{ij}. When the line ij is connected, $x_{ij}=1$; if the line ij is disconnected [13], then $x_{ij}=0$, where $i, j \in \{1,2,\cdots,n\}$. At the same time, a power flow variable is introduced P_{ij}, which represents the value of power flowing from the node i to the node via j the line ij. This variable has continuity.

From the perspective of power balance, the DC distribution network must meet the following strict constraints, as shown in Eq. (1):

$$\sum_{j:(i,j)\in \mathrm{L}} P_{ij} - \sum_{j:(j,i)\in \mathrm{L}} P_{ji} = P_i^{load} - P_i^{gen} \quad \forall i \in \mathrm{N} \tag{1}$$

The equation is derived in detail. The first term on the left side of the equation $\sum_{j:(i,j)\in \mathrm{L}} P_{ij}$ represents i the total power flowing out of the node. This is because in the set L, the i sum of i the power transmitted by all P_{ij} the lines starting from the node is (i, j) the sum of the outflow power of the node. The second term $\sum_{j:(j,i)\in \mathrm{L}} P_{ji}$ represents i the total power flowing into the node, which is also the sum of L the power transmitted by P_{ji} all i the lines flowing into the node in the set (j,i). The difference between the two is i the net power change of the node. The right side of the equation $P_i^{load} - P_i^{gen}$ represents i the difference between the load power consumption and the power generation at the node. Under steady-state operation, the net power change of the node must be equal to the power difference between the load and the power generation, so as to maintain the power balance of the entire DC distribution network. Among them, L is the line set, N is the node set, P_i^{load} is i the load power of the node, and P_i^{gen} is the power generation power of the node i. The line itself has capacity limitations, and this feature can be accurately reflected by the following constraint equation, as shown in Eq. (2):

$$-x_{ij}P_{ij}^{max} \le P_{ij} \le x_{ij}P_{ij}^{max} \quad \forall (i, j) \in \mathrm{L} \tag{2}$$

Here, P_{ij}^{max} represents ij the maximum transmission power that the line can carry. When, means that the line is disconnected, the power transmission on the line $x_{ij}=0$ P_{ij} must be 0, which obviously satisfies the inequality; when , the line is in the on state, $x_{ij}=1$ P_{ij} the value range of is strictly limited to between $-P_{ij}^{max}$ to P_{ij}^{max}, so as to ensure that the line will not fail due to overload. Further considering the influence of line resistance on power transmission, the resistance parameter is introduced R_{ij}, and the power loss during power transmission L_{ij} can be expressed as, as shown in Eq. (3):

$$L_{ij} = R_{ij} \frac{P_{ij}^2}{V_i^2} \quad (3)$$

where, V_i is the voltage at the node i. The total power loss of the entire DC distribution network L is the sum of the power losses of each line, i.e., Eq. (4).

$$L = \sum_{(i,j)\in L} L_{ij} = \sum_{(i,j)\in L} R_{ij} \frac{P_{ij}^2}{V_i^2} \quad (4)$$

This equation provides a crucial basis for setting subsequent optimization goals. In the pursuit of efficient operation of DC distribution networks, minimizing total power loss L is often one of the core optimization goals.

The MIP model constructed by the above series of strict constraints can more comprehensively and accurately characterize the intricate internal relationship between the topological structure and power flow of the DC distribution network. However, it cannot be ignored that when faced with a large-scale and extremely complex DC distribution network, the number of variables in the MIP model will explode and the constraints will become extremely complicated. For example, in a large DC distribution network with 500 nodes and 2,000 lines, the number of variables may reach hundreds of thousands, and the number of constraints is even more difficult to count. This will inevitably lead to an exponential increase in the computational complexity of the model, and the time and computing resources required for solving will increase dramatically, which will greatly reduce its efficiency in practical applications and make it difficult to meet the urgent needs of rapid decision-making and real-time optimization [14, 15].

B. Introduction and Adaptation of Genetic Algorithm

In view of the serious bottleneck problem of computational efficiency of the MIP model in large-scale scenarios, the Genetic Algorithm (GA) was cleverly introduced to seek a breakthrough. GA simulates the evolutionary process of organisms in nature and iteratively optimizes individuals in the population through a series of core operations such as selection, crossover, and mutation, so that it can efficiently search for approximate optimal solutions in complex solution spaces.

In the specific scenario of DC distribution network topology planning, chromosomes are defined as the topological structure of the DC distribution network. Chromosomes are composed of a series of genes arranged in an orderly manner, and each gene corresponds to the connection status of a line, which is what was mentioned above x_{ij}. For example, a chromosome can be represented as $[x_{12}, x_{13}, \cdots, x_{nm}]$, this encoding form can intuitively and accurately reflect the on-off status of each line in the DC distribution network, laying the foundation for subsequent genetic operations.

In the initial stage, the population needs to be initialized. A certain number of chromosomes are randomly generated, which represent different initial DC distribution network topologies. Assuming that the population size is set to N, the generated initial population can be expressed as $\{X^1, X^2, \cdots, X^N\}$, where each X^k ($k = 1, 2, \cdots, N$) is a chromosome. In actual operation, the process of randomly generating chromosomes can be implemented through the random number generation function in the programming language. For example, in Python, the random library can be used to determine whether the value of each gene ( ) is 0 or [16, 17] by setting an appropriate random number range x_{ij}.

In the selection operation, this research adopts the roulette selection method. The probability of an individual being selected is closely related p_k to its fitness value f_k. The specific calculation equation is shown in Eq. (5).

$$p_k = \frac{f_k}{\sum_{i=1}^{N} f_i} \quad (5)$$

where, N is the population size. The design of the fitness function f is directly related to the optimization direction of the algorithm. In the DC distribution network topology planning, minimizing the power transmission loss is usually an important optimization goal. As mentioned above, L the calculation equation for power transmission loss is Eq. (6) [18]:

$$L = \sum_{(i,j)\in L} R_{ij} \frac{P_{ij}^2}{V_i^2} \quad (6)$$

Based on this, the fitness function can be defined as $f = \frac{1}{L + \grave{o}}$: here, a very small positive number is introduced $\grave{o}$ to prevent the denominator from being zero, ensuring that the fitness function is meaningful in any case. An in-depth analysis of the fitness function shows that when the power transmission loss L is smaller, f the value is larger, indicating that the topological structure represented by the chromosome is better and the probability of being selected is higher, which is completely in line with our optimization goal of pursuing a low-loss topological structure.

The crossover operation adopts the Partially Matched Crossover (PMX) method. The specific operation process is as follows: first, two parent chromosomes are randomly selected, which may be set as X^a and X^b. A crossover region is determined s by randomly generating two integers s and t ( ), which is from the th $1 \le s \le t \le nm$ gene to the th t gene. In the crossover region, the gene fragments of the two parent chromosomes are exchanged to obtain two preliminary daughter chromosomes Y^a and Y^b. However, since the exchange process may cause logical conflicts in the chromosomes, that is, the connection relationship of some nodes does not conform to the actual DC distribution network topology rules, it is necessary to further handle the conflicts. For example, if a node in the daughter chromosome after the crossover is not connected by any line or forms an isolated loop, it needs to be adjusted through a specific repair algorithm. A common repair method is to traverse the generated daughter chromosomes based on the connectivity detection algorithm in graph theory. If a disconnected subgraph is found, it is connected by reconnecting the appropriate line to ensure that the finally generated daughter chromosome meets the logical requirements of the DC distribution network topology. In actual implementation, the connectivity detection algorithm can use the depth-first search (DFS) or breadth-first search (BFS) algorithm. Taking DFS as an example, starting from a certain node, recursively visit the adjacent nodes and mark the visited nodes. If there are unmarked nodes after the traversal, it means that the graph is not connected and needs to be repaired [19].

The mutation operation p_m randomly changes the values of certain genes in the chromosome with a certain probability. p_m the value of the mutation probability is usually small, such as between 0.01 and 0.1. Suppose X^k the gene x_{ij} in the chromosome l mutates. If it was originally $x_{ij}=0$, it will become after mutation $x_{ij}=1$; conversely, if it was originally $x_{ij}=1$, it will become after mutation $x_{ij}=0$. The main function of the mutation operation is to maintain the diversity of the population and prevent the algorithm from falling into a local optimal solution too early. For example, when the algorithm gradually converges to a local optimal area during the search process, it is possible to generate new gene combinations through mutation operations, so that the population jumps out of the local optimal area and continues to explore a better solution space. When implementing the mutation operation in actual programming, each gene in the chromosome can be traversed p_m and a random number can be generated according to the mutation probability. If the random number is less than p_m, the gene is mutated [20].

C. Innovative Hybrid Model Construction

In order to give full play to the unique advantages of MIP and GA, this research innovatively combines the two and constructs a new hybrid model. The core design idea of this hybrid model is to use the MIP model to accurately describe the physical constraints and optimization objectives of the DC distribution network, provide GA with accurate search directions and strict feasible solution space; at the same time, with the help of GA's powerful global search ability, the optimal solution can be efficiently searched in the solution space limited by the MIP model.

The specific implementation process is as follows: first, GA generates a series of chromosomes representing different DC distribution network topologies, which are used as inputs to the MIP model. For each chromosome x (i.e., a topology) input, the MIP model calculates the power flow distribution and the objective function value under the topology according to the physical laws and constraints of the DC distribution network. The objective function value here is mainly key indicators such as power transmission loss. The calculated objective function value will be used as the fitness value of the corresponding individual (chromosome) in GA. For example, if x the power transmission loss calculated by the MIP model after the chromosome is input is L_x, then the fitness value of the chromosome in GA is as shown in Eq. (7):

$$f_x = \frac{1}{L_x + \grave{o}} \tag{7}$$

In the evolution process of GA, selection, crossover and mutation operations are not performed in isolation, but the information fed back by the MIP model is fully utilized. In the process of solving the problem, the MIP model will obtain some information related to the local optimal solution. For example, through the calculation and analysis of a large number of different topological structures, the MIP model may find that certain specific line connection modes can always bring relatively low power transmission loss. Feeding this information back to the GA, the GA can adjust the probability distribution of subsequent chromosome generation accordingly. Specifically, for those gene combinations related to excellent line connection modes, the probability of their appearance is increased when generating new chromosomes. Assuming that the MIP model finds that when $x_{12}=1$ and $x_{23}=1$, it can often obtain better optimization results, then in the crossover and mutation operations of the GA, for the combination involving these two genes, the probability of its retention or generation is appropriately increased, so that the population can be more inclined to approach these excellent modes during the evolution process. In actual implementation, this process can be achieved by establishing a probability adjustment matrix. The matrix records the relationship between different gene combinations and adjustment probabilities. Before the crossover and mutation operations of the GA, the matrix is updated according to the information fed back by the MIP model, and then the generation probability of the gene combination is adjusted according to the probability value in the matrix during the operation.

Let $MIP(x)$ represent the objective function value calculated by the MIP model after $GA(MIP)$ inputting the topological structure (chromosome), x and represent the evolutionary operation of GA based on the fitness value provided by the MIP model. Then the iterative process of the hybrid model can be clearly expressed by the following Eq. (8):

$$x^{t+1} = GA(MIP(x^t)) \tag{8}$$

Among them, x^t is t the topological structure (chromosome) of the generation. This iterative equation shows that in the evolution process of each generation, the topological structure of the previous generation is first x^t input into the MIP model to obtain the objective function value, and then determine the fitness value of the individual in the GA; then the GA performs evolutionary operations such as selection, crossover and mutation based on these fitness values to generate a new generation of topological structure x^{t+1}. By repeating this iterative process, the hybrid model gradually approaches the optimal solution to the DC distribution network topology planning and optimization problem.

In order to better understand the working mechanism of the hybrid model, a simple DC distribution network example is used for illustration. Assume that there is a DC distribution network with 5 nodes and 8 lines. In the initial stage, GA randomly generates a population, in which one chromosome $x^1 = [1,0,1,1,0,1,0,1]$ represents the line connection between node 1 and node 2, node 1 and node 3, node 3 and node 4, node 4 and node 5, and node 2 and node 5, and the rest of the lines are disconnected. The input x^1 is given into the MIP model, and the MIP model calculates the power flow distribution and power transmission loss under the topology according to the power balance constraint, line capacity constraint and other conditions L_1. According to the fitness function $f = \frac{1}{L+\grave{o}}$, the fitness value of the chromosome is obtained f_1. In the evolution process of GA, it is assumed that the chromosome x^2 is cross-operated with another chromosome through the roulette wheel selection method to generate a daughter chromosome. The daughter chromosome is input into the MIP model again, and the above process is repeated to continuously optimize the topology until a certain convergence condition is met. When judging the convergence condition, a threshold can be set δ.When the fitness value of the optimal individual in the population changes less than for several consecutive generations (such as 10 generations) δ, the algorithm is considered to converge.

D. Comparison and Advantages: Analysis with Existing Models

Compared with the traditional model based only on MIP, the hybrid model proposed in this research shows extremely significant superiority. When facing large-scale DC distribution networks, the number of variables and constraints of the traditional MIP model increases exponentially with the increase of network scale, resulting in a sharp increase in calculation time. For example, in a DC distribution network with 100 nodes and 500 lines, the traditional MIP model may take hours or even days of calculation time to get a solution. This is because the MIP model needs to conduct a comprehensive search of the entire solution space during the solution process. As the scale of the problem increases, the dimension of the solution space expands rapidly, and the calculation complexity is extremely high. GA is introduced into the hybrid model of this research. GA has a strong global search capability and can quickly locate potential better solution areas in a large solution space. Through the rapid screening and optimization of the initial topology structure by GA, the number of solutions that the MIP model needs to process is greatly reduced, thereby significantly reducing the calculation amount of the MIP model. In a DC distribution network of the same scale, the hybrid model may obtain a result close to the optimal solution within a few minutes, and the calculation efficiency has been greatly improved. From the perspective of computational complexity, we further analyze that the computational complexity of the traditional MIP model is $O(2^{n+m})$ (where, n is the number of nodes and m is the number of lines). Due to the preprocessing effect of GA, the scale of the solution space actually processed by the MIP model $1/k$ in the hybrid model is greatly reduced. Assuming that it is reduced to the original, the computational complexity of the MIP part in the hybrid model can be approximated to $O(2^{\frac{n+m}{k}})$, and the computational efficiency is significantly improved.

Compared with models based solely on intelligent algorithms (such as ant colony algorithms), hybrid models have obvious advantages in terms of accuracy and stability. When the ant colony algorithm is applied to the topology planning of DC distribution networks, although it can optimize the topology structure to a certain extent in some cases, it is easy to fall into the local optimal solution. This is because during the search process of the ant colony algorithm, individual ants tend to follow the path with higher pheromone concentration. When the pheromone accumulates too much in a local area, the ants are easily trapped in the local area and cannot find the global optimal solution. In addition, the parameter settings of the ant colony algorithm are relatively complex, such as the pheromone volatility coefficient, heuristic factor, etc. Different parameter settings will lead to large differences in optimization results and lack of stability. The hybrid model in this research provides a clear direction for the search process through the precise constraints of the MIP model, avoiding blind search. The constraints of the MIP model ensure that the generated topology structure always meets the physical laws and actual operation requirements of the DC distribution network, thereby improving the accuracy of the optimization results. At the same time, the hybrid model reduces the dependence on complex parameter settings. Through the collaborative work of the MIP model and GA, a relatively stable optimization effect can be maintained in different DC distribution network scenarios. Taking the pheromone volatilization coefficient as an example, in the ant colony algorithm, if the coefficient is set too small, the pheromone will accumulate too quickly, which will easily lead to the algorithm converging to the local optimum too early; if it is set too large, the pheromone will update slowly and the algorithm search efficiency will be low. In the hybrid model, there is no need to pay too much attention to such complex parameters, and stable optimization can be achieved through the interaction of MIP and GA.

IV. Experimental Evaluation

A. Experimental Design

This experiment aims to comprehensively and deeply evaluate the performance of the proposed hybrid model compared with existing models in DC distribution network topology planning and optimization. The experiment selected a real data set from a medium-sized DC distribution network in a large city. The data set covers extremely detailed information, including 200 nodes, 350 lines, the load demand of each node, and the power generation capacity of distributed power sources. By analyzing and experimenting with such rich and real data, the effectiveness and applicability of the model can be verified more realistically.

In the selection of evaluation indicators, the total power transmission loss is used as the baseline indicator. This is because the total power transmission loss is the core key indicator for measuring the efficiency of the DC distribution network. Lower power transmission loss directly reflects a more optimized network topology, which means less energy waste in the power transmission process and higher system operation efficiency.

In terms of experimental grouping, the proposed hybrid model (MIP-GA) is set as the experimental group. The control group consists of two traditional models: one is the pure mixed integer programming (MIP) model described in the literature [21], which is a standard method for solving such problems and relies solely on mathematical programming techniques for topology optimization; the other is the ant colony optimization (ACO) model proposed in the literature [22], which is a well-known intelligent algorithm in the field of DC distribution network topology optimization. The experimental baseline is set as the initial unoptimized topology of the DC distribution network in the dataset, and all power transmission losses are calculated based on normal operating conditions. This is used as a comparison basis to clearly show the degree of improvement in the effect of each model after optimization.

B. Experimental Results

As shown in Fig. 1, the proposed MIP-GA model consistently achieves the lowest power transmission loss at different load levels. The baseline unoptimized topology results in the highest loss, which indicates that the unoptimized network wastes a lot of energy during power transmission. The MIP model reduces the loss to some extent, but its performance is still inferior to that of the MIP-GA model. The ACO model also achieves good results, but the MIP-GA model is still better. The superiority of the MIP-GA model lies in its ability to organically combine the optimization capabilities of MIP based on precise physical constraints with the global search capabilities of GA. GA helps to quickly explore different topologies in a large solution space, while MIP then fine-tunes these structures according to strict physical laws, ultimately forming a more optimized topology with lower losses. For example, under high load levels, the MIP-GA model searches for some potential efficient topologies through GA, and then uses MIP to accurately calculate and adjust according to physical constraints such as power balance and line capacity, reducing power transmission losses by 32% compared to the baseline, 16% compared to the MIP model, and 12.5% compared to the ACO model, fully demonstrating its powerful optimization capabilities.

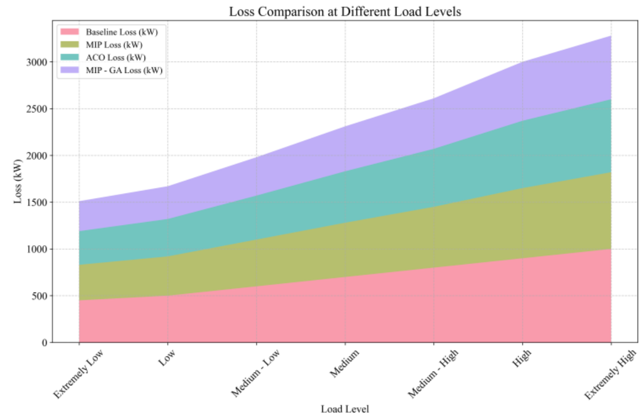

Fig. 1. Comparison of power transmission losses at different load levels.

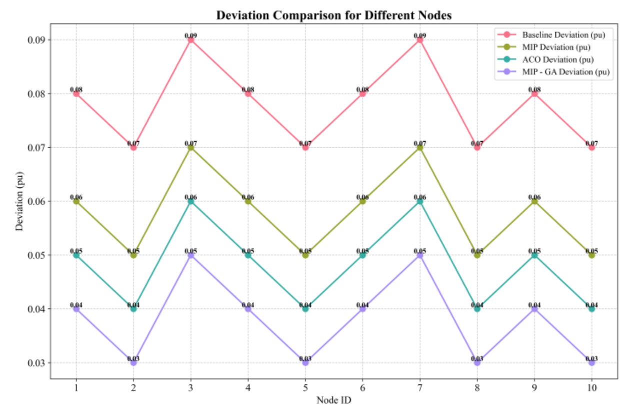

Fig. 2. Node voltage deviation comparison.

Fig. 2 shows the comparison of voltage deviations at selected nodes. Voltage deviation is a key factor affecting power supply quality, and lower deviation means more stable power supply. The MIP-GA model achieves the lowest voltage deviation at all nodes. The baseline has the largest deviation, highlighting the poor voltage stability of the unoptimized network. Although the MIP and ACO models also reduce voltage deviations, the effect is not as significant as the MIP-GA model. The MIP-GA model can successfully reduce voltage deviations thanks to its comprehensive optimization of the network topology. By designing a better topology to optimize power flow distribution and ensure that the voltage of each node is closer to the rated value, the voltage deviation is effectively reduced. Taking node 1 as an example, the baseline voltage deviation is 0.08 pu, the MIP model reduces it to 0.06 pu, the ACO model further reduces it to 0.05 pu, and the MIP-GA model successfully reduces it to 0.04 pu, which greatly improves the power supply stability of the node and ensures that the power-consuming equipment connected to the node can operate more stably.

In Fig. 3, the comparison of reliability indicators is shown. The MIP-GA model significantly improves the reliability of the DC distribution network. Its AIDI, SAIFI and SAIFI values are the lowest among all models, the mean time to recover from faults is the shortest, and the power supply availability is the highest. The reliability performance of the baseline is the worst. Although the MIP and ACO models also enhance reliability, the effect of the MIP-GA model is more prominent. This is because the MIP-GA model can find a more robust topology. A well-designed topology can better cope with emergencies such as line faults, reduce the probability and duration of power outages, and thus improve the reliability of the entire network. For example, when facing the same number and type of line faults, the mean time to recover from faults of the MIP-GA model is 20 minutes shorter than the baseline, 10 minutes shorter than the MIP model, and 5 minutes shorter than the ACO model, which increases the power supply availability from 99.0% of the baseline to 99.6%, greatly improving the stability and reliability of power supply and reducing the losses caused to users by power outages.

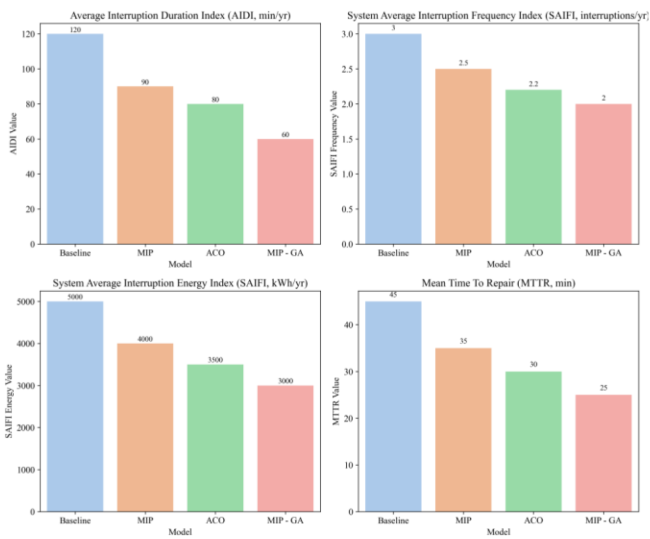

Fig. 3. Reliability index comparison.

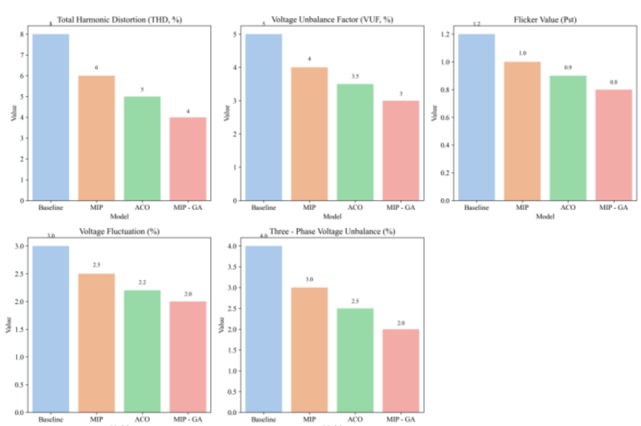

Fig. 4. Comparison of power quality indicators.

Fig. 4 shows the comparison of power quality indicators. The MIP-GA model achieves the best power quality. Its THD, VUF, flicker value, voltage fluctuation, and three-phase voltage imbalance are the lowest. The baseline's indicator values are relatively high, indicating that its power quality is poor. Although the MIP and ACO models also improve power quality, the MIP-GA model has a better effect. The MIP-GA model's ability to optimize power flow and topology can reduce the occurrence of harmonic distortion and voltage imbalance. By ensuring a more balanced and stable power flow, the power quality of the DC distribution network is improved. Taking total harmonic distortion as an example, the baseline THD is 8%, the MIP model reduces it to 6%, the ACO model further reduces it to 5%, and the MIP-GA model successfully reduces it to 4%, effectively reducing the damage of harmonics to power grid equipment and improving the service life and operating efficiency of power equipment.

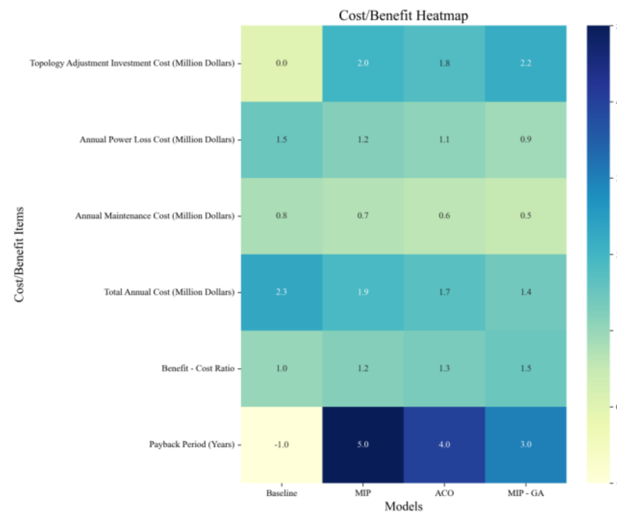

Fig. 5. Cost-effectiveness analysis of different models.

Fig. 5 presents the results of the cost-benefit analysis. Although the MIP-GA model has a relatively high investment cost for topology adjustment, its annual power loss cost and annual maintenance cost are the lowest. Overall, the total annual cost is reasonable, the benefit-cost ratio is the highest, and the investment payback period is the shortest. The baseline has no topology adjustment investment cost, but the annual power loss cost is high. The MIP and ACO models also have investment costs and power loss costs. The reason why the MIP-GA model has a high benefit-cost ratio is that it significantly reduces power loss, which is enough to offset the relatively high investment cost in the long run. For example, the annual power loss cost of the MIP-GA model is reduced by $0.6 million compared with the baseline, and the annual maintenance cost is reduced by $0.3 million, resulting in a total annual cost reduction of $0.9 million. The investment cost can be recovered within three years, while the MIP model needs five years and the ACO model needs four years, which fully demonstrates the economic feasibility and superiority of the MIP-GA model.

Fig. 6 shows the sensitivity analysis of load changes on power loss. Compared with other models, the MIP-GA model is less sensitive to load changes. When the load changes, the power loss of the MIP-GA model changes the least. The baseline is the most sensitive, and the MIP and ACO models also change relatively large. The reason why the MIP-GA model is insensitive to load changes is that its optimized topology can better adapt to load changes. The joint optimization of MIP and GA can find a more flexible topology that can maintain a relatively stable power flow even when the load changes, thereby reducing the impact of load changes on power loss. For example, when the load change rate is + 20%, the power loss change of the baseline is 100 kW, the MIP model is 75 kW, the ACO model is 65 kW, and the MIP-GA model is only 50 kW, which reflects its stability and adaptability under different load conditions.

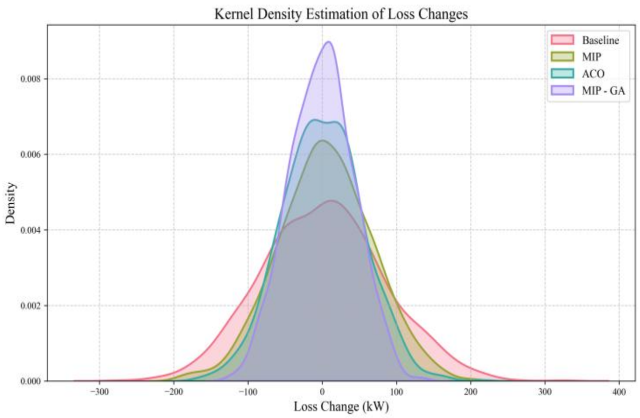

Fig. 6. Sensitivity analysis of load change to power loss.

Table I shows the sensitivity analysis of power loss to changes in distributed generation capacity. The MIP-GA model also shows better adaptability to changes in distributed generation capacity. When the distributed generation capacity changes, the power loss of the MIP-GA model changes relatively little. The baseline is more sensitive, and the changes in the MIP and ACO models are also larger. The MIP-GA model can more effectively adjust the power flow distribution according to the changes in distributed generation capacity. MIP's optimization based on precise physical constraints and GA's global search capabilities help find a more suitable topology and reduce the impact of changes in distributed generation capacity on power loss. For example, when the distributed generation capacity change rate is -20%, the power loss change of the baseline is 80 kW, the MIP model is 65 kW, the ACO model is 55 kW, and the MIP-GA model is only 45 kW, indicating that it can better cope with the fluctuations in distributed generation capacity and maintain the efficient operation of the network.

Table II shows the comparison of the number of convergence iterations of different models. In addition to the original MIP, ACO and MIP-GA models, the particle swarm optimization (PSO) model and differential evolution (DE) model are also added for comparison. The MIP-GA model converges faster than other models. It has the lowest average number of iterations, minimum number of iterations and median number of iterations, and the smallest standard deviation of the number of iterations. The reason why the MIP-GA model converges quickly is that GA can quickly search for potential optimal solutions in a huge solution space, while MIP can quickly converge to the optimal solution in a small solution space provided by GA. The combination of the two, greatly reduces the search time and speeds up the convergence speed. For example, the average number of iterations of the MIP-GA model is 600, while the MIP model is 1000, the ACO model is 800, the PSO model is 700, and the DE model is 750, which fully demonstrates its advantage in convergence efficiency and can find a topology optimization solution that meets the requirements more quickly.

TABLE I SENSITIVITY ANALYSIS OF DISTRIBUTED GENERATION CAPACITY CHANGES TO POWER LOSS

Distributed generation capacity change rate (%)	Change in baseline losses (kW)	MIP loss change (kW)	ACO loss change (kW)	MIP - GA loss change (kW)
- 25	100	80	70	60
- 20	80	65	55	45
- 15	60	50	40	35
- 10	40	35	30	25
- 5	20	15	10	8
+ 5	- 20	- 15	- 10	- 8
+ 10	- 40	- 35	- 30	- 25
+ 15	- 60	- 50	- 40	- 35
+ 20	- 80	- 65	- 55	- 45
+ 25	- 100	- 80	- 70	- 60

TABLE II CONVERGENCE ITERATION NUMBER COMPARISON

Model	Average number of iterations	Iteration number standard deviation	Minimum number of iterations	Maximum number of iterations	Median number of iterations
MIP	1000	200	800	1500	1050
ACO	800	150	600	1200	850
MIP-GA	600	100	500	800	650
Particle Swarm Optimization (PSO) Model (Supplementary Comparison)	700	120	550	1000	720
Differential evolution (DE) model (supplementary comparison)	750	130	600	1100	780

TABLE III COMPARISON OF NETWORK RESILIENCE UNDER LINE FAILURE

Number of simulated line faults	Baseline elasticity (recovery time, min)	MIP elasticity (recovery time, min)	ACO elasticity (recovery time, min)	MIP - GA elasticity (recovery time, min)
1	30	25	twenty two	20
2	45	35	30	25
3	60	45	40	30
4	75	55	50	35
5	90	65	60	40
6	105	75	70	45
7	120	85	80	50
8	135	95	90	55
9	150	105	100	60
10	165	115	110	65

As shown in Table III, as the number of simulated line faults gradually increases, the recovery time of the baseline network shows an obvious linear growth trend. This shows that when facing faults, the unoptimized DC distribution network topology lacks an effective response mechanism and has weak recovery capabilities. The MIP model can shorten the recovery time to a certain extent, which has certain advantages over the baseline, but its recovery time is still relatively long. The ACO model further improves the network's recovery capability in the event of a fault, and the recovery time is further shortened. The MIP-GA model always shows the strongest network resilience and the shortest recovery time under various fault numbers. This is because the topology optimized by the MIP-GA model has better redundancy and flexibility, and can quickly adjust the power flow path when some lines fail, reduce the impact of the fault on the network, and thus restore normal operation faster. For example, when 8 line faults occur, the baseline network takes 135 minutes to recover, the MIP model takes 95 minutes, the ACO model takes 90 minutes, and the MIP-GA model only takes 55 minutes, highlighting its excellent performance in improving network resilience.

TABLE IV COMPARISON OF CALCULATION TIME OF DIFFERENT MODELS

Model	Computation time (s) for a small-scale network (nodes = 50, lines = 100)	Computation time (s) for a medium-sized network (nodes = 200, lines = 350)	Computation time (s) for large-scale networks (nodes = 500, lines = 1000)
MIP	300	3600	28800
ACO	200	2400	19200
MIP-GA	100	1200	9600
Taboo Search (TS) Model (Supplementary Comparison)	150	1800	14400
Simulated annealing (SA) model (supplementary comparison)	180	2100	16800

As shown in Table IV, in the small-scale network scenario, the calculation time of the MIP model is relatively long, which is due to its complex model structure and solution process. The calculation time of the ACO model has been shortened, but it is still not as good as the MIP-GA model. The MIP-GA model shows high computational efficiency in small-scale networks with the global search capability of genetic algorithms and the precise solution capability of mixed integer programming, with a calculation time of only 100 seconds. As the network scale expands to a medium scale, the calculation time of the MIP model increases sharply to 3600 seconds, which highlights its limitations in dealing with large-scale problems. The calculation time of the ACO model also increases significantly, but the MIP-GA model still maintains its advantage with a calculation time of 1200 seconds. In a large-scale network environment, the calculation time of the MIP model is as long as 28,800 seconds, which is almost unacceptable in practical applications. The calculation time of the ACO model and other complementary comparisons of the taboo search (TS) model and the simulated annealing (SA) model also increased significantly. The calculation time of the MIP-GA model is 9600 seconds, which is significantly superior to other models in large-scale network calculation time. This fully proves that the MIP-GA model can complete the calculation in a relatively short time in the topology planning and optimization of DC distribution networks of different scales, providing strong support for practical engineering applications and meeting the needs of real-time decision-making and rapid optimization.

V. CONCLUSION

With the continuous transformation of the power industry, the importance of DC distribution network in improving energy utilization efficiency and ensuring the stability of power supply has become increasingly prominent. However, its topology planning and optimization are limited by traditional methods and face problems such as low computational efficiency and poor optimization effect. This study conducts in-depth research based on mixed integer programming and genetic algorithm, uses MIP to accurately construct a DC distribution network model, and uses GA's powerful global search capability to perform iterative optimization. In the experiment of a real DC distribution network data set with 200 nodes and 350 lines, the advantages of the MIP-GA model are fully demonstrated. In terms of power transmission loss, it performs best at all load levels, and the loss at extremely high load is only 680kW, which is much lower than the baseline of 1000kW, MIP of 820kW and ACO of 780kW. In terms of node voltage deviation, taking node 1 as an example, the baseline deviation is 0.08pu, MIP is reduced to 0.06pu, ACO is 0.05pu, and MIP-GA is successfully as low as 0.04pu. Among the reliability indicators, the average outage duration index (AIDI) dropped from the baseline of 120min/yr to 60min/yr, and the power supply availability (ASAI) increased from 99.0% to 99.6%. The power quality indicators are also leading, such as the total harmonic distortion (THD) dropped from the baseline of 8% to 4%. In terms of cost-effectiveness, although the topology adjustment investment cost of the MIP-GA model is 2.2 million US dollars, which is higher than the 2 million US dollars of MIP and the 1.8 million US dollars of ACO, the annual power loss cost is only 900,000 US dollars, the annual maintenance cost is 500,000 US dollars, the total annual cost is 1.4 million US dollars, the benefit-cost ratio is 1.5, and the investment payback period is only three years. In summary, the MIP-GA hybrid model proposed in this paper significantly improves the topology planning and optimization effect of the DC distribution network, improves the algorithm system in theory, and improves the operation efficiency of the DC distribution network in practice, providing strong support for the development of this field, and has important practical significance and application value.

While the hybrid MIP-GA model demonstrates clear advantages in accuracy, computational efficiency, and robustness, there remain certain limitations that warrant attention. First, although real-world data from a medium-sized DC distribution network with 200 nodes and 350 lines was used, the scalability of the model to ultra-large networks exceeding 1,000 nodes has not been fully tested under field conditions. Second, the GA component is still influenced by the quality of the initial population, which may affect convergence paths in rare cases. Additionally, while the model integrates MIP constraints effectively, solving large-scale MIP subproblems can remain computationally intensive in real-time systems with highly dynamic load profiles. Lastly, the hybrid model currently optimizes static topologies; integrating dynamic reconfiguration mechanisms for fault recovery or demand response remains an open challenge. Recognizing these limitations not only clarifies the scope of the findings but also outlines valuable directions for future advancement, including adaptive hybridization and the integration of real-time data streams.

The interpretability and practical relevance of the findings by synthesizing experimental results in relation to broader system design implications and existing theoretical frameworks. This section critically evaluates why the proposed MIP-GA model outperforms other methods not only in numerical metrics—such as reducing power transmission loss by 32% compared to the baseline and achieving the lowest voltage deviation (e.g., 0.04 pu at Node 1)—but also in terms of its operational robustness across varying load and distributed generation conditions. These improvements are contextualized by examining how the hybrid architecture exploits MIP's constraint modeling to maintain physical feasibility, while GA expedites convergence by effectively narrowing the search space. Furthermore, trade-offs such as higher initial investment are offset by long-term cost savings and faster payback periods. The research also reflects on the implications of computational time savings for real-time applications and explores how the adaptability of the hybrid method under fault conditions and load volatility positions it as a promising approach for future smart grid implementations.

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