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Multi-Objective Optimization Method for MVD Systems Based on Wireless Networks

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Abstract The MVD (medium voltage distribution) network is the link connecting users in the power system. The MVD network has many lines and users, and traditional optimization methods are difficult to ensure the economy of reactive power compensation and reduce distribution network (DN) losses at the same time. This article constructed a MVD system based on wireless networks and optimizes it through multi-objective genetic algorithm (MOGA), considering the compensation economy of the DN and ensuring power supply quality. This article used a large number of wireless sensor devices to collect DN data, and transmits the collected information to the control center through Zigbee wireless technology. MOGA is used for optimization. This article used genetic algorithms to generate initial populations and continuously generate new offspring populations through crossover and mutation, in order to improve the fitness and quality of population reconciliation. This paper tested the IEEE (Institute of Electrical and Electronics Engineers) 33 node DN model. The unit investment benefit and DN loss after multi-objective genetic optimization in the IEEE33 node DN model were 0.67 yuan and 210kW, respectively; the unit investment benefit and DN loss optimized by traditional optimization algorithms were 0.58 yuan and 222kW, respectively. Multi objective genetic optimization of MVD systems based on wireless networks can simultaneously consider the economy of reactive power optimization and DN losses, meeting the optimization requirements of MVD systems.

Index Terms Multi-Objective Optimization, MVD Systems, Wireless Networks, Genetic Algorithms, Reactive Power Optimization Planning

I. Introduction

The development of society and people's lives are inseparable from the use of electricity, and the power system includes power generation, transmission, distribution, and consumption. With the increasing demand for electricity, maintaining the safety of power supply in the power system has become very important. The power distribution process is to supply the electricity received by the power supply side to the user end, and the working state of the power distribution directly affects the stability and safety of the power grid. The MVD system provides electricity to users through MVD lines and distribution stations. The DN is the most prone link to faults, and over 95% of power outages for Chinese power users are caused by distribution faults. With the increasing demand for electricity from users, the scale and complexity of DN have also become increasingly high. Distribution losses are inevitable in the process of providing electricity to users. The traditional optimization method for DN is to minimize network losses. Due to the large number of lines and users in the MVD network, it is difficult to ensure the economic efficiency and power supply quality of the DN. With the development of wireless network technology, real-time MVD data can be collected by installing wireless sensing devices, and the MVD system can be comprehensively considered through multi-objective optimization. Through MVD optimization planning, power supply quality can be ensured and DN losses can be reduced.

The DN receives electricity from the transmission network and distributes it to users. The MVD system is a commonly used power grid, with a large number of lines and an important component of the power grid system. Shah, Maqsood Ahmad developed an improved filter based on mathematical morphology to quickly and clearly extract the transient information in the energy signal in the form of positive/negative polarity. The polarity detection of any disturbance in the energy signal he analyzed indicates the occurrence of sudden disturbances in the system, thereby providing high-speed protection against rapidly rising short circuit faults in the MVD system [1]. Moutis, Panayiotis used digital dual distribution transformers for real-time monitoring of medium voltage in low-voltage measurements. He conducted real-time monitoring of the distribution system by calculating the waveform of voltage and current, as well as active and reactive power [2]. Gu, Hanwen proposed a comprehensive small-signal model of DC distribution system based on voltage source converter, which considered all controllers of AC (alternating current) filter, DC (direct current) distribution cable and voltage source converter. By establishing an absolutely stable synchronous rotating coordinate system to eliminate the influence of short-circuit ratio in the AC system, the proposed model is used to ensure the safety of the MVD system [3]. Chang, Jae-Won's research points out that voltage power sensitivity plays a crucial role in the control and operation of DN, and he proposes a new data-driven sensitivity estimation method. This method considers the multidimensional sensitivity of MVD networks, which is estimated by solving a nonlinear least squares problem to achieve accurate estimation. The effectiveness of this method has been verified using a real-time platform [4]. The circuit of the MVD system is complex and has a large number of users. Data monitoring of the MVD system is beneficial for ensuring the stability of the power grid, but there is a lack of wireless network to collect MVD data.

With the rapid development of wireless networks, real-time data information can be collected using wireless sensing devices. Many people use wireless networks to collect data from MVD systems, achieving automatic monitoring and control. Liu, Jianming proposed an application system for monitoring, inspection, security, and interactive services in hierarchical transmission and distribution systems, which meets the monitoring and operational requirements of the transmission and distribution system through wireless sensor network technology [5]. The working state of the MVD system directly affects the stability and safety of the power grid. Qiao, Lei proposed a new unified control method that only utilizes local measurements to improve the stability of DC voltage and AC frequency, and achieve coordinated control between MVD centers and flexible interconnected microgrids [6]. Lavanya, S. proposed a new signal processing method with low sampling rate, high signal processing speed, low computational and storage requirements for detecting high impedance faults in MVD networks. This method can process signals very quickly, with a low sampling rate and reduced memory and computational workload [7]. Lv, Wenxuan proposed a backup protection acceleration strategy based on inverter fault control. The current is first controlled by the fault control of the converter to ensure fault characteristics during backup protection. Then, the DC switch on the healthy line is blocked by the polarity of the current integration, and the DN enters closed-loop mode to provide a fault current path [8]. The use of wireless networks can obtain real-time data information of MVD systems, but there is a lack of applying multi-objective optimization algorithms to MVD systems.

The MVD system has a large number of circuit lines and users, and traditional MVD data collection has problems such as poor communication ability and low reliability. This article collects real-time MVD data through wireless sensor devices and optimizes it through MOGA. This article simulates an actual DN example, and the results show that the multi-objective optimization method proposed in this paper can simultaneously reduce DN losses and improve investment returns on reactive power compensation.

II. Method for Establishing a Wireless Network-Based MVD System

As a fundamental resource related to the national economy and people's livelihood, the lives of individuals are significantly impacted practically by the electricity system functioning normally. The demand for electricity in society is constantly increasing, and the scale of the power network is becoming larger and larger.

The overall process of the power system can be divided into power generation, transmission, distribution, and consumption. The DN is a very important load center in the power system and the tail end of power production. The DN directly determines the quality of electricity consumption for users [9], [10]. The DN ensures the reliability of user power supply by distributing electrical energy. As the economy developed and the people's electricity consumption increased, the social electricity load is constantly increasing, making it even more difficult to achieve power supply stability. The structural model of the power network is displayed in Figure 1.

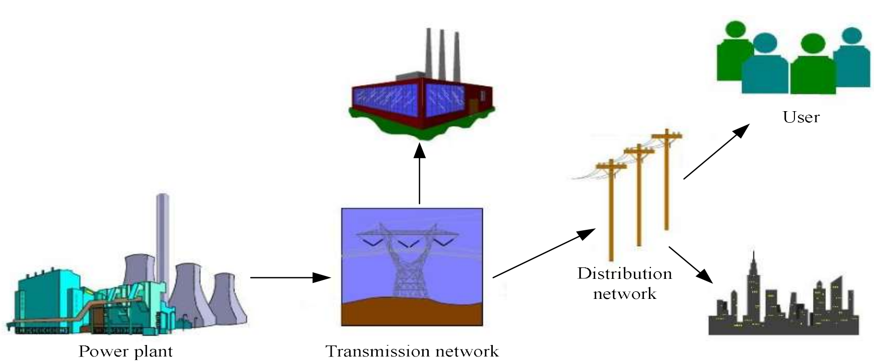

Figure 1: Structural model diagram of power network

In Figure 1, the structural model of the power network is described, where electricity is processed by power plants, transmission networks, and DN before being transmitted to the user end, providing reliable electricity for the user.

The DN can be divided into high-voltage distribution, MVD, and low-voltage distribution according to the size of distribution voltage [11]. The voltage range in high-voltage distribution is between 110kV and 500kV, while the voltage range in MVD is between 10-35kV. MVD is a common form of distribution with characteristics such as multiple users, multiple lines, and wide coverage. Once the MVD network encounters a fault, it would cause huge economic losses to the power grid company and society.

With the increasing demand for electricity from Chinese users, there are many problems in the construction process of the DN system. The reliability of the DN is poor: Most of China's DN are powered by a single power source, and once the power supply fails, it would cause local power outages. The severe losses in the DN: China's DN has multiple branches, long power supply lines, and multiple components and equipment on the lines, which cause significant losses in the DN. Low automation level of DN: China's DN construction speed is slow, unable to timely collect and process data in the DN, making it difficult to achieve DN automation.

With the development of wireless networks, wireless sensors can be used to collect data from MVD systems and achieve DN automation through real-time processing. The steps to build a MVD system based on wireless networks are as follows:

II. A. Wireless Sensor Equipment Collects Data

A wireless sensor network is composed of many wireless sensors, which can be monitored in real-time within a certain area through a certain connection method [12], [13]. Sensor nodes transmit data through wireless communication, resulting in low transmission energy consumption and high transmission efficiency [14], [15]. The structure of the MVD system based on wireless networks is displayed in Figure 2.

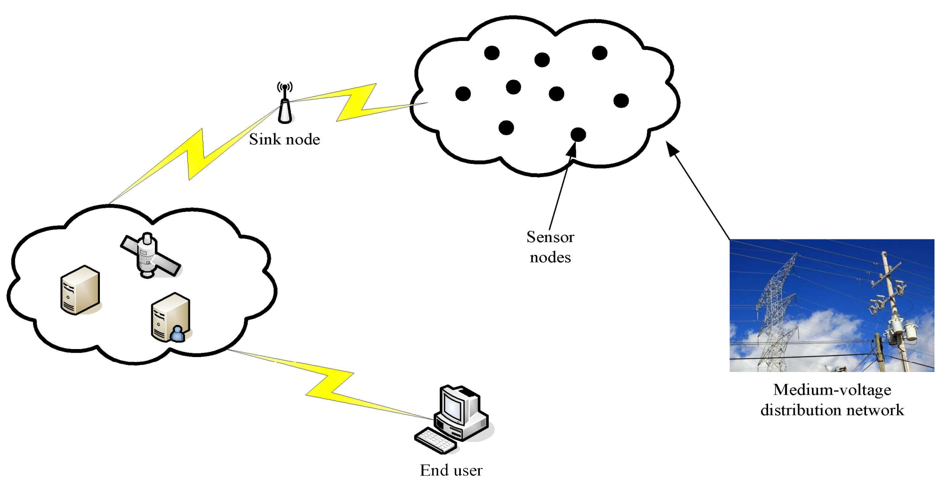

Figure 2: Structure of MVD system based on wireless network

In Figure 2, the structure of a MVD system based on wireless networks is described. A large number of wireless sensor devices are installed in the MVD network, and the MVD information collected by sensors is transmitted to end users through aggregation nodes and wireless network transmission.

Wireless sensor devices can be installed in the MVD network to transmit the collected data to the control center through wireless communication technology, thus achieving MVD data collection.

II. B. Real Time Data Transmission

The data collected by sensors needs to be transmitted through wireless communication technology, as the data volume of MVD is very large, and the analysis of MVD information needs to ensure timeliness. Therefore, it is necessary to ensure that the collected data can be transmitted in real-time. Common wireless communication technologies are displayed in Table 1.

Table 1: Comparison of wireless communication technologies

Performance	Wireless fidelity	Bluetooth	Zigbee
Working frequency	2.4GHz		
Price	Expensive	Cheap	Cheap
Communication distance	100-300m	2-30m	50-300m
Power dissipation	High	Low	Low
Security	Low	High	High
Stability	Low	Medium	High

In Table 1, three common wireless communication technologies are described, and the communication performance of Wireless Fidelity, Bluetooth, and Zigbee is compared. Zigbee has a low price, long communication distance, high security and stability, making it very suitable for use in MVD systems.

This article uses Zigbee communication technology to achieve real-time transmission of MVD data, and timely transmit the data collected by wireless sensors to the control center.

II. C.Multi Objective Optimization

In the MVD network, due to the large number of branches and users, MVD is prone to losses [16]. It is not comprehensive to only consider the network losses of the MVD network, and it also needs to consider the investment benefits and safety of reactive power compensation in the MVD network.

MVD optimization is a comprehensive optimization process that allows for multi-objective analysis of real-time MVD data collected. It optimizes the MVD system with the goal of minimizing active power loss and maximizing the investment return of reactive power compensation units through optimization algorithms, thereby improving the operational efficiency of the MVD network and ensuring the power supply safety of users.

The active network loss in the DN refers to the sum of the active losses of each branch line in the DN, expressed as:

$$P_{loss} = \sum_{j=1}^{n} I_j^2 R_j \quad (1)$$

The process of reactive power compensation is to improve the power factor of the power grid, thereby reducing circuit losses in the DN. This paper selects the node with the largest active power loss for reactive power compensation by using the data of the MVD network collected by the sensor, and analyzes the economic efficiency, until the benefit of reducing network loss after compensation is greater than the economy of reactive power compensation investment.

The interface of the MVD system based on wireless network is displayed in Figure 3.

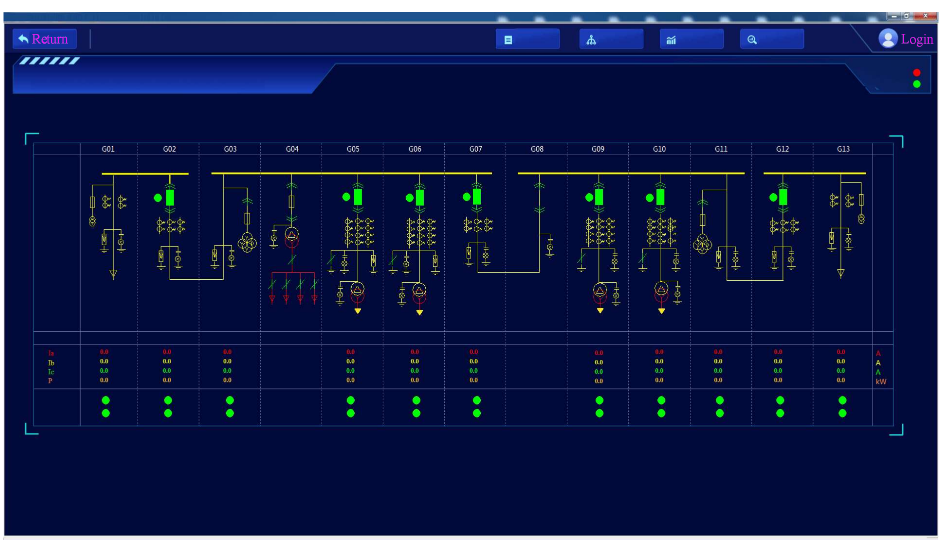

Figure 3: Interface of MVD system based on wireless network

In Figure 3, a MVD system based on wireless networks is described. Staff can query the topology structure of the MVD system through backend login and monitor its status in real-time.

III. MOGA Optimization

In order to achieve collaborative optimization of multi-objective factors in the MVD system, MOGA is used to optimize losses in the MVD process. Genetic algorithm is an optimization search algorithm commonly used in mathematics, which is developed based on biological evolution phenomena and seeks the optimal solution through the mechanism of survival of the fittest [17], [18].

Genetic algorithm can be well applied to multi-objective optimization problems, conducting global search through multiple iterations to obtain the optimal solution [19], [20]. MOGA can be used to collect data from the MVD system for optimization, thereby reducing losses in the MVD process. The specific implementation process of multi-objective optimization of MVD data using MOGA is displayed below.

III. A. Generate Initial Population

In this paper, wireless sensor is used to collect the capacity of compensation capacitor in MVD network, and decimal integer code is used to represent the capacity of compensation capacitor, so that the code of the ith individual is $S_i = [C_1, C_2, \cdots, C_m]$. It randomly generates an initial population with a length of m. The concept of population in genetic algorithms is to imitate the process of biological inheritance, and population is a subset in the search space.

III. B. Determination of Individual Fitness

The fitness of an individual is the standard for measuring their strengths and weaknesses, and it can be used to determine whether an individual can inherit. The judgment method for individual fitness is:

$$(\mathrm{i_a} < \mathrm{j_a}) \text{ or } ((\mathrm{i_a} = \mathrm{j_a}) \text{ and } (\mathrm{i_b} > \mathrm{j_b})) \tag{2}$$

In Formula 2, i and j are two individuals respectively; $\mathrm{i_a}$ represents the unoccupied rank of individual i; $\mathrm{i_b}$ represents the estimated density of individual i.

So for two individuals, individuals with lower unoccupied ranks are better, or when the unoccupied ranks are the same, individuals with higher density estimates are better.

III. C. Cross and Variation

In genetic algorithms, crossover and mutation are two important operations. Through crossover and mutation, the diversity of the population can be effectively improved, leading to more effective algorithm search. In the early stages of evolution, high-order genes are generally selected as intersections, while in the later stages of evolution, low-order genes are generally selected as intersections. The process of selecting intersections is displayed below.

$$P_r = a + {}^{b}\!/_{1 + exp(t(g - g_0))} \tag{3}$$

In Formula 3, P_r represents the probability of selecting high-order gene intersections, g represents evolutionary algebra, and a, b, t, g_0 represent the constants.

The probability of selecting the intersection of low order genes is expressed as:

$$P_t = 1 - P_r \tag{4}$$

Similarly, the probability of selecting high-order gene mutations is expressed as:

$$P_{r1} = a_1 + {}^{b_1}\!\Big/_{1 + exp(t_1(g - g_0'))} \tag{5}$$

In Formula 5, P_{r1} represents the probability of selecting high-order gene mutation points, and a_1, b_1, t_1, g_0' represent the constants.

The probability of selecting low order gene mutations is expressed as:

$$P_{r2} = a_2 + {}^{b_2}\!\Big/_{1 + exp(-t_1(g - g_0'))} \tag{6}$$

In Formula 6, P_{r2} represents the probability of selecting low order gene mutation points, and a_2, b_2, t_1, g_0' represent the constants.

III. D. Elite Retention

Elite retention refers to the retention of excellent individuals in the parent generation, which combines the parent generation and all descendants in the parent generation into a population, calculates the distance between individuals in the population, and sorts them. Excellent elites in the population can be retained and new offspring populations can be formed through operations such as crossover and mutation.

III. E. Adaptive Encoding

In the MVD network, there are many branch lines and many nodes for loss compensation. When the compensation capacity calculated using genetic algorithm is small, it is possible to adaptively adjust individual coding without compensation.

The normal operation of the DN is the key to ensuring the quality of user power supply, but the large number of branch lines and multiple households in the DN leads to serious losses in the DN. This article constructs a MVD system based on wireless networks, which collects real-time information from the MVD network through wireless sensors. It is optimized with the goal of minimizing active power loss and maximizing investment return on reactive power compensation.

MOGA can perform parallel analysis on populations, achieving multi-directionality and global search by maintaining a population composed of potential solutions between generations. The MOGA can be well applied to wireless network-based MVD systems for comprehensive optimization of MVD networks.

IV. Experiment on Multi-Objective Optimization of MVD System

The MVD network is the electrical part directly connected to users, providing them with electricity by distributing voltage that meets the conditions. In addition to providing electricity to users, the DN also needs to ensure the quality of electricity supply. The voltage range in MVD is 10-35kV, but there are many branch lines in the MVD network, which can easily lead to energy loss. Once the DN malfunctions, it would lead to widespread power outages at the user end, seriously affecting the power supply effect.

The traditional optimization method for MVD systems is to construct membership functions for fuzzy evaluation of voltage, and achieve single objective DN optimization by reducing data uncertainty. The optimization points in MVD network systems are often not single, and multi-objective optimization is required. It is necessary to consider both the loss situation of the DN and the investment income of reactive power compensation in the DN. Traditional optimization methods are difficult to achieve multi-objective optimization of MVD systems.

In order to effectively achieve multi-objective optimization of the MVD network, this paper constructs a MVD system based on wireless networks. Wireless sensors are used to collect real-time data information of the MVD network, and the collected data is transmitted to the control center for optimization analysis. This article utilizes MOGA for optimization, achieving global optimization by crossing and mutating the population.

This article would compare traditional single objective optimization and MOGA optimization for MVD systems based on wireless networks. In the MOGA, the population size is selected as 100, the number of iterations is 100, and the single group capacity of the capacitor is 10kvar, $a_1 = 0.01$, $b_1 = 0.01$, $a_2 = 0.01$, $b_2 = 0.05$, $g_0' = 60$, $t_1 = 0.04$. This article uses an IEEE33 node DN model for testing, with a total of 32 branch lines and a reference voltage of 12kV.

The data of the first 8 branches in the IEEE33 node DN model is displayed in Table 2.

Table 2: IEEE33 node DN model data

Branch number	Starting node	End node	Electric resistance (Ω)
1	0	1	0.092
2	1	2	0.487
3	2	3	0.422
4	3	4	0.389
5	4	5	0.921
6	5	6	0.231
7	6	7	0.722
8	7	8	1.122

In Table 2, the first 8 branches of the IEEE33 node DN model are described with data, and the resistance of each branch node is different.

The IEEE33 node DN model is displayed in Figure 4.

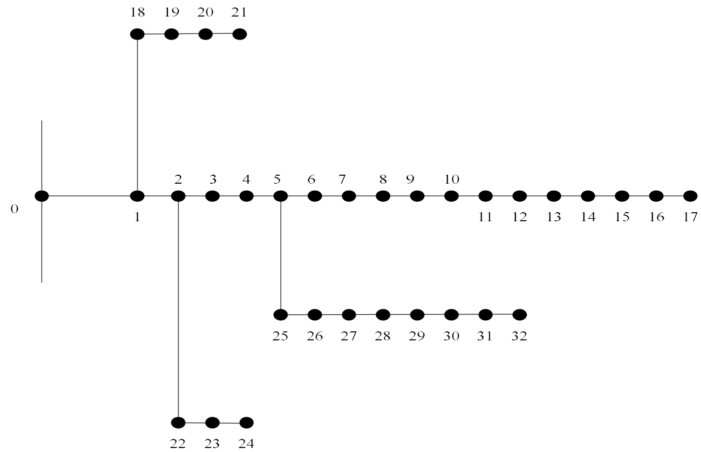

Figure 4: IEEE33 node DN model

In Figure 4, the IEEE33 node DN model is described, with a total of 33 nodes and 32 branches. The effectiveness of multi-objective optimization can be analyzed through the IEEE33 node DN model.

In the MVD system, optimization is aimed at minimizing losses and maximizing investment returns for reactive power compensation. The MVD network system needs to meet the comprehensive requirements of operational quality and economic benefits. This article also conducts optimization calculations on a 10kV MVD network with 116 actual nodes, and compares traditional single objective optimization and MOGA optimization. In order to accurately analyze the optimization effect, this article set up 10 sets of experiments to test the optimization effects of different algorithms, and the final optimization effect was taken as the average of 10 sets of data.

V. Multi-Objective Optimization Results of MVD System

V. A. IEEE33 Node DN Model Optimization

This article uses a multi-objective genetic optimization algorithm to optimize the IEEE33 node DN, aiming to find the optimal solution with the goals of grid loss and reactive power compensation investment return. This article analyzes the solution space under the initial population and the solution space after 100 generations of evolution, and calculates the solution set of unit investment benefits and DN losses.

(1) Solution space under initial population

The solution space under the initial population is displayed in Figure 5.

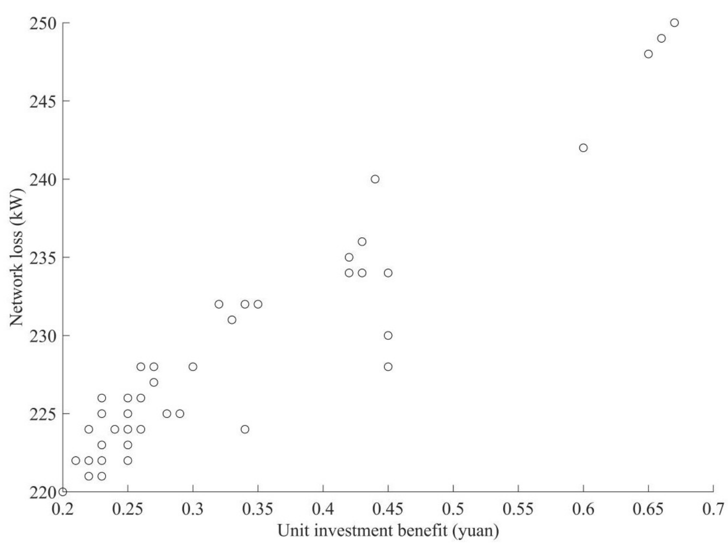

Figure 5: Solution space under initial population

In Figure 5, the solution space under the initial population is described. In the solution set with a unit investment benefit of less than 0.5 yuan, the vast majority of DN losses are less than 240kW. In the concentration where the unit investment benefit is greater than 0.5 yuan, all DN losses are greater than 240kW. It can be seen that the solution space under the initial population cannot simultaneously meet the goals of low power grid losses and high investment returns for reactive power compensation. This is mainly because the initial population optimization of genetic algorithms is very easy to fall into local optima, making it difficult to perform global optimization.

(2) Solution space after 100 generations of evolution

After undergoing operations such as crossover and mutation, multi-objective genetic optimization can undergo iterative evolution. The solution space after 100 generations of evolution is displayed in Figure 6.

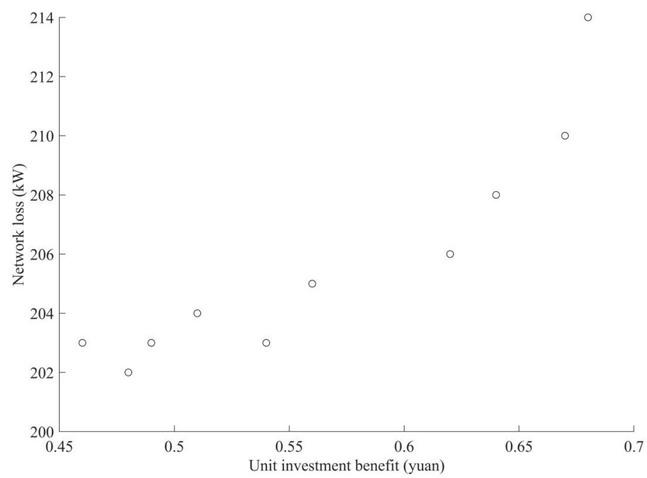

Figure 6: Solution space after 100 generations of evolution

In Figure 6, the solution space after 100 generations of evolution is described, with the horizontal axis representing unit investment benefits and the vertical axis representing DN losses. After 100 generations of evolution, the maximum loss in the DN was 214kW. There were 3 solutions where the unit investment benefit was less than 0.5 yuan, and 7 solutions where the unit investment benefit was greater than 0.5 yuan. This indicates that after 100 generations of evolution, solutions with high unit investment efficiency and low DN losses can be found simultaneously. The multi-objective genetic optimization algorithm achieves global optimal solution by retaining the excellent elites in the parent generation. The use of multi-objective genetic optimization algorithms can obtain multiple Pareto optimal solutions, providing data reference for workers in MVD systems. Efforts should be made to reduce losses in the MVD network and increase investment returns on reactive power compensation.

V. B. Comparison between Traditional Optimization Algorithms and Multi-Objective Genetic Optimization Algorithms

The traditional optimization algorithm for MVD systems is to construct membership functions for optimization. This article compares the optimization results of traditional optimization algorithms with multi-objective genetic optimization algorithms, and analyzes the compensation points, compensation capacity, unit investment benefits, and network losses of IEEE33 node DN. The comparison results between traditional optimization algorithms and multi-objective genetic optimization algorithms are displayed in Table 3.

Table 3: Comparison results between traditional optimization algorithms and multi-objective genetic optimization algorithms

Optimization algorithm	Compensation node	Compensation capacity (kvar)	Unit investment benefit (yuan)	Network loss before optimization (kW)	Optimized network loss (kW)
Multi-objective genetic optimization	3	360	0.67	250	210
	7	1000			
	23	540			
Traditional optimization algorithm	4	950	0.58	250	222
	22	600			
	26	250			

In Table 3, the comparison results between traditional optimization algorithms and multi-objective genetic optimization algorithms are described. The compensation nodes of multi-objective genetic optimization algorithms were 3, 7, and 23. The compensation capacity was 360kvar, 1000kvar, and 540kvar, respectively. The unit investment benefit of multi-objective genetic optimization was 0.67 yuan. The DN loss before optimization was 250kW, and the DN loss after optimization was 210kW. It can be seen that the multi-objective genetic optimization algorithm can effectively reduce the loss of the DN after optimization, and the loss of the DN has been reduced by 40kW. The unit investment benefit of traditional algorithms was 0.58 yuan. The DN losses before and after optimization were 250kW and 222kW, respectively. Traditional optimization algorithms can also reduce network losses to a certain extent. The network loss optimized by traditional optimization algorithms is higher than that of multi-objective genetic optimization, and the unit investment efficiency of traditional optimization algorithms is lower than that of multi-objective genetic optimization algorithms. Therefore, in the IEEE33 node DN model, the use of multi-objective genetic optimization algorithm can more effectively reduce losses in the MVD network and improve the return on reactive power compensation investment.

V. C. Actual Engineering Examples

In actual MVD networks, the number of nodes is very large, and multi-objective optimization of MVD networks is extremely important. This article optimizes the 10kV MVD network with 116 nodes in practical engineering.

(1) Single objective optimization results

Single objective optimization refers to the use of traditional optimization algorithms for minimizing DN losses or maximizing reactive power compensation investment returns. The results of single objective optimization are displayed in Table 4.

Table 4: Single objective optimization results

Optimization objectives	Compensation node	Compensation capacity (kvar)	Unit investment benefit (yuan)	Network loss before optimization (kW)	Optimized network loss (kW)
Maximum investment return on reactive power compensation	8	990	1.21	380	332
	11	1100			
	66	160			
Minimum loss in DN	7	1020	0.92	380	321
	14	1460			
	72	110			

In Table 4, the single objective optimization results are described, and two objectives of optimization have been carried out for the 10kV MVD network in actual engineering. In the optimization process aimed at maximizing the investment return of reactive power compensation, the unit investment benefit reached 1.12 yuan, and the loss of the DN was reduced from 380kW to 332kW. The optimization aimed at maximizing the return on reactive power compensation investment aims to maximize the unit investment efficiency as much as possible, but the optimization of DN losses is not significant. In the optimization process aimed at minimizing the loss of the DN, the selected compensation nodes were 7, 14, and 72, with compensation capacities of 1020kvar, 1460kvar, and 110kvar, respectively. The optimization method with the goal of reducing network losses can significantly reduce DN losses, reducing them from 380kW to 321kW. However, the unit investment efficiency under the optimization method with the smallest DN losses was not very high, with a unit investment efficiency of 0.92 yuan. Therefore, a single objective optimization method is difficult to simultaneously maximize the reduction of DN losses and improve the investment income of reactive power compensation.

(2) Optimization results of MOGA

MOGA optimization is a compromise consideration of multiple optimization objectives, which selects the comprehensive optimal result through operations such as crossover and mutation on the population. The results of MOGA optimization are displayed in Figure 7.

In Figure 7, the results of MOGA optimization are described. The horizontal axis represents the group of optimization experiments. This article conducted a total of 10 sets of data tests. The left vertical axis represents the unit investment benefit, while the right vertical axis represents the DN loss. The unit investment efficiency reached a minimum of 1.01 yuan in the fifth group and a maximum of 1.42 yuan in the first group; the average unit investment benefit was 1.227 yuan. The average DN loss was 326.8kW. MOGA optimization can comprehensively optimize unit investment benefits and DN losses. Compared to single objective optimization, MOGA optimization is a compromise optimization method that can effectively reduce DN losses while ensuring high unit investment efficiency, thereby ensuring the operational quality and economic benefits of the MVD network.

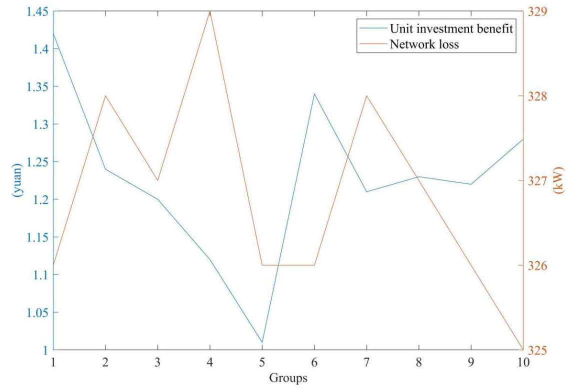

Figure 7: Results of MOGA optimization

VI. Conclusions

The MVD network is a link that directly supplies power to users, and the operational efficiency of the DN directly affects the quality of electricity consumption by users. The MVD network has many branch lines and a large number of connected users, which leads to losses during operation. People's requirements for the operation of MVD networks are constantly improving. When optimizing network losses, other factors need to be considered, such as economic indicators such as investment efficiency. This article used wireless networks to establish a MVD system, collected a large amount of MVD network data in real-time through sensor devices, and transmitted the data back to the control center. This article used MOGA to optimize the collected MVD network information, and conducted optimization analysis on the IEEE33 node DN model and the actual MVD network of 116 nodes. In the IEEE33 node model, MOGA can find solutions to reduce DN losses and improve investment returns of reactive power compensation after 100 evolutions. In practical examples of MVD networks, MOGA optimization is a compromise between various single objective optimizations, while meeting the requirements of investment economy and reducing DN losses in MVD network systems. The optimization of the MVD system in this article only considered two aspects: network loss and compensation investment return, and the analyzed objectives are not comprehensive. Therefore, conducting more optimization analysis on the MVD system would be the direction of future research.

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