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# Distribution network monitoring and management system based on intelligent recognition and judgement

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### Abstract

Based on the shortcomings of the current intelligent management of distribution networks, the article designs and implements a remote intelligent detection system for live distribution networks. The article constructs and realises an algorithm based on a genetic algorithm (GA) and agent system. The algorithm is applied to energy-saving intelligent supervision of equipment in the distribution network. The simulation experiment shows that the integrated algorithm based on GA and agent system can accurately detect power quality in real time. At the same time, the algorithm can monitor the energy consumption of equipment in the distribution network under multiple disturbances.

**Keywords:** intelligent identification and judgement, distribution network, energy saving and consumption reduction, monitoring management, genetic algorithm.
**AMS 2010 codes:** 17D92

## 1 Introduction

Energy conservation has become a long-term strategic policy for Chinese economic and social development, and power conservation is an integral part of the national energy conservation strategy. At present, the energy-saving technology of enterprise distribution networks has the following shortcomings: 1) The entire distribution network lacks overall planning and management methods, and the energy management level is not high. At present, the distribution network has not formed an 'all-round and multifaceted' comprehensive energy saving and consumption reduction strategy. 2) The enterprise distribution network is only partially optimised and managed, which has significant limitations. 3) The energy-saving equipment of the enterprise power distribution network is still in a single operation. This has formed a situation of 'isolated islands', resulting in scattered

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information and low integration [1]. Such a situation is not convenient for high-level management and control. 4) The energy-saving equipment of a single independent node influences other nodes. Once the local regulation is excessive or insufficient, it causes the fault of the adjacent line to form a ‘critical area’. 5) A single energy-saving device only has only a particular aspect of the energy-saving function, which cannot meet the needs of society for energy saving in all aspects. In addition, the independent control of energy-saving equipment quickly leads to too frequent equipment adjustments. The service life of power distribution equipment is shortened, and maintenance costs increase.

An agent is an entity that can perceive, solve problems and communicate with the outside world. A multi-agent system (MAS) is a network structure composed of multiple loosely coupled, coarse-grained, perceptual, problem-solving agents that are able to communicate with other agents in the system. While taking into account the advantages of a single-agent system, MAS accomplishes complex control tasks or solves complex problems through negotiation, coordination and collaboration.

A genetic algorithm (GA) is an adaptive global optimisation algorithm formed by simulating living beings’ genetic and evolution processes in the natural environment. This paper combines the GA and the MAS technology to construct a multi-agent genetic optimisation algorithm, namely the GA-MAS. The algorithm uses the agent’s local perception, competition, cooperation and self-learning characteristics to achieve biological adaptation to the environment. Because all operations act instead of the entire population, the diversity of the population is maintained [2]. This suppresses the premature phenomenon of GAs to a certain extent.

Because of the above-mentioned shortcomings of the existing technology and its existing defects, we combined the GA and the MAS technology to propose a comprehensive management system for energy-saving and consumption-reducing distribution networks based on a multi-agent genetic optimisation algorithm, i.e. the GA-MAS. The article gives the basic structural model of the management system and the energy-saving equipment multi-agent structural model. The article uses the GA-MAS algorithm to get the best adjustment intensity of energy-saving equipment. This enables the energy-saving equipment to obtain the maximum energy-saving benefit with the minimum adjustment cost. The simulation of specific examples and practical engineering applications show that the management system proposed in this paper can reduce the total active power loss and the total number of capacitor input groups [3]. At the same time, this also shows that the GA-MAS algorithm has good computational efficiency and convergence stability.

## 2 The reactive power optimisation model

In actual engineering applications, reactive power compensation devices inevitably produce active power loss and operation and maintenance costs. In addition, when the reactive power resources of the distribution network are insufficient, we need to add reactive power compensation equipment, which generates additional investment [4]. Therefore, the system needs to comprehensively consider the minimum total investment of the reactive power compensation device while pursuing the minimum active power loss to establish the objective function:

$$min f_{Q1} = \sum_{i=1}^{n} Q_{ci}(\Delta P_C CT + K_1) + C\Delta Pt \tag{1}$$

$$\Delta P = \sum_{i=1}^{N} V_i \sum_{j\in i} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \tag{2}$$

Here, $N$ is the number of system nodes, $n$ is the number of nodes installed with reactive power compensation devices, $Q_{Ci}$ is the reactive power compensation capacity on node $i$, $\Delta P_C$ is the active power loss per $kVar$ reactive power compensation capacity and $C$ is the feed-in tariff [5]. Further, $T$ is the number of operating hours per year, $K_1$ is the annual operation and maintenance cost of the capacitor, $\Delta P$ is the active power loss of the system and $t$ is the maximum load-operating time per year; $V_i$ and $V_j$ refer to the voltage amplitudes of nodes $i$ and $j$, respectively; $G_{ij}$ and $B_{ij}$ respectively refer to the mutual admittance elements (transconductance, mutual admittance) of the network admittance matrix; and $\theta_{ij}$ refers to the phase difference of node voltage.

$$min f_{Q2} = \sum^{m} c_{ui} \Delta u \tag{3}$$

$\Delta u$ is the amount of change of the control variable. $m$ is the number of compensation devices and $c_{ui}$ is the adjustment cost of the $i$ device. Taking the transformer as an example, the cost is $A_{cost}$ yuan. The total number of tap adjustments allowed is $T_n$ times. The life expectancy when the tap is never adjusted is 1 year [6]. After $T_n$ times of tap adjustment, the life is shortened to $a'$ years. The increased operation and maintenance workload for adjusting the equipment is $B$. Then, the adjustment cost (yuan/time) for each operation of the tap of the transformer is represented as follows:

$$c_{u1} = B + (a - c')A_{cost}/aT_n \tag{4}$$

From Eq. (4), the adjustment cost of the switching switch of the reactive power compensation device can be calculated similarly. The mathematical model of objective optimisation is as follows.

1) Objective function

$$F_Q = f_{Q1} + f_{Q2} \tag{5}$$

2) Equality constraints

$$\begin{cases} P_i = V_i \sum_{j \in i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \\ Q_i = V_i \sim_{j \in i} V_j (G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) \end{cases} \tag{6}$$

3) Inequality constraints

$$V_{i\,min} < V_i < V_{i\,max} \tag{7}$$

$$\begin{cases} Q_{CiSVC\,min} < Q_{CiSVC} < Q_{CiSVC\,max} \\ Q_{CiHAPF\,min} < Q_{CiHAPF} < Q_{CiHAPF\,max} \\ Q_{CiIVC\,min} < Q_{CiIVC} < Q_{CiIVC\,max} \\ Q_{CiDSTATCOM\,min} < Q_{CiDSTATCOM} < Q_{CiDSTATCOM\,max} \\ T_{i\,min} < T_i < T_{i\,max} \\ Q_{Gimin} < Q_{Gi} < Q_{Gimax} \end{cases} \tag{8}$$

$V_i$ is the voltage of node $i$. $Q_{CiSVC}, Q_{CiHAPF}, Q_{CiIVC}$ and $Q_{CiDSTATCOM}$ are the reactive power compensation capacities of $SVC, HAPF, IVC$ and $DSTATCOM$ respectively. $T_i$ is the tap position of the on-load tapping transformer. $Q_{Gi}$ provides reactive power for the generator.

## 3 The GA-MAS approach

### 3.1 Agent's environment

The multi-agent optimisation GA is an algorithm that combines the main features of the GA and MAS. We first construct the living environment of the Agent. Each Agent interacts with its neighbourhood [7]. Combined with the evolution mechanism of the GA, experiments enable it to converge to the optimal global solution quickly and accurately. We equate any agent $\alpha$ to a body in the GA. Its fitness value is as follows:

$$f(a) = F_Q \tag{9}$$

The purpose of Agent $\alpha$ is to reduce its fitness value as much as possible while meeting the constraints of the operating conditions. All agents are put into a living environment, i.e. an $L \times L$ grid. Among them, $L = \sqrt{N}, N$ and $N$ are the number of individuals in the group. As shown in Figure 1, each agent 'lives' in the environment and is fixed in a grid. Each Agent has its life cycle and self-learning ability [8]. It can perceive individuals in its neighbourhood and autonomously take action based on the perceived information to complete its intentions and goals. Each Agent and its neighbours constitute the local environment of the Agent. The dashed frame constitutes the local environment of Agent 2 and 2. Each Agent only mates with other agents in the neighbourhood to produce new individuals. It has a particular locality. And other individuals in its neighbourhood mate with individuals in its neighbourhood. Due to the overlapping of neighbourhoods, there is information exchange between all individuals to maintain the group's diversity.

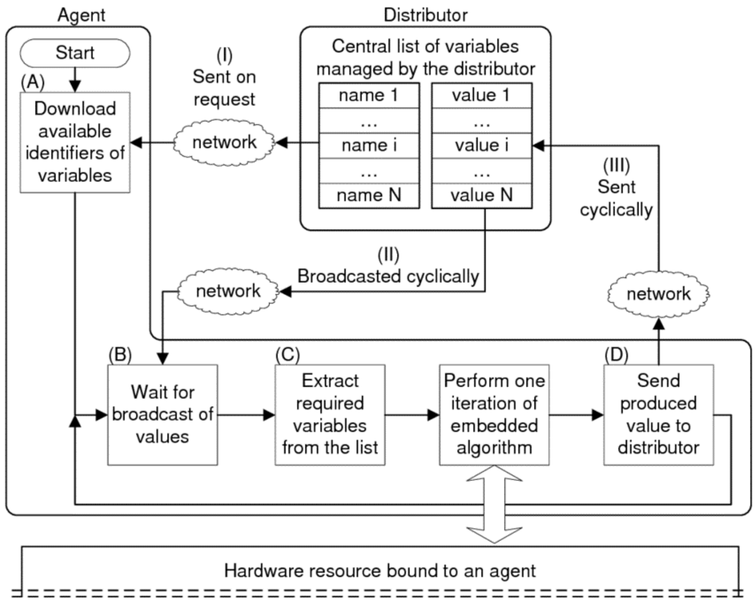


**Fig. 1** The environment structure diagram of an Agent.

### 3.2 Flow chart of the GA-MAS algorithm

The flowchart of the GA-MAS algorithm is shown in Figure 2.

#### 3.2.1 Pareto preferential operation

Each Agent searches for the optimal solution according to its local environment and its neighbours. In the local environment of any agent, if the individual is better than other surrounding individuals, then the individual is the Paleto optimal solution in its neighbourhood [9]. Since selecting the best is performed in the local environment of each individual, it ensures the diversity of the group.

#### 3.2.2 Mating operation

We assume that the two parents involved in mating are $P1 = (p_{1,1}, \cdots, p_{1,n}), P1 = (p_{2,1}, \cdots, p_{2,n})$, and the parent solution space is $[m_p, n_p]$, and

$$m_p = [min(p_{1,1}, p_{2,1}), \cdots, min(p_{1,n}, p_{2,n})] \tag{10}$$

$$n_p = [max(p_{1,1}, p_{2,1}), \cdots, max(p_{1,n}, p_{2,n})] \tag{11}$$

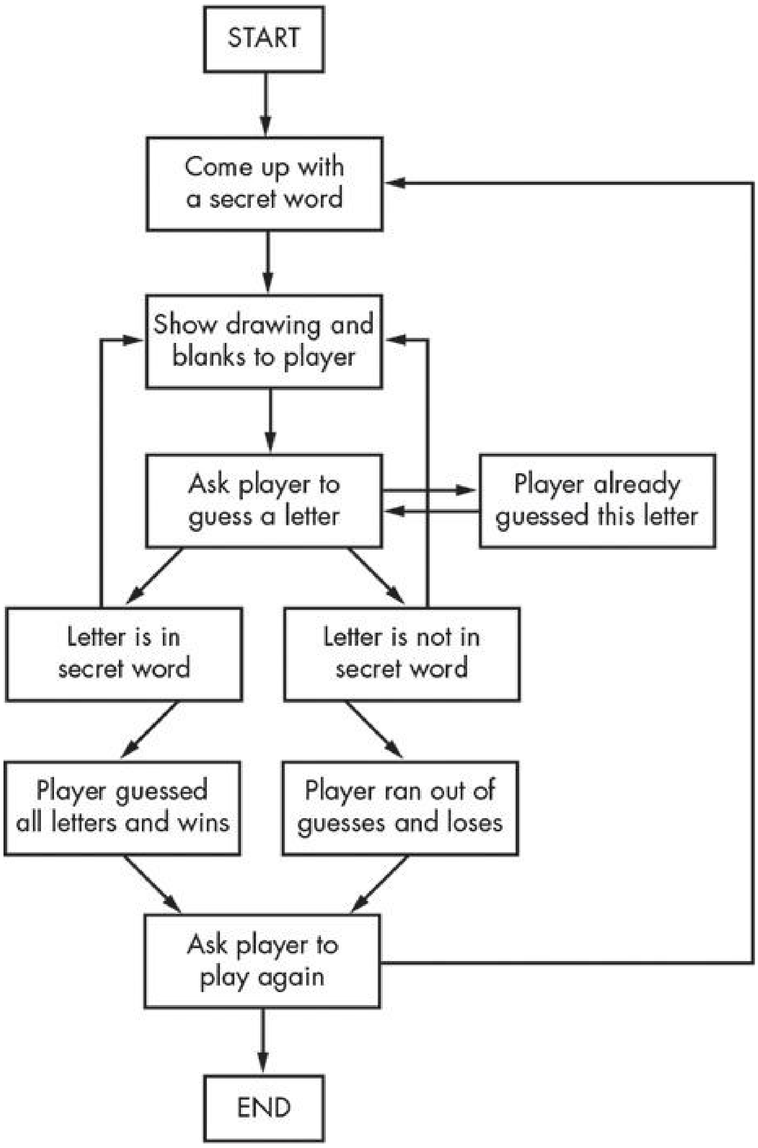


**Fig. 2** Flowchart of the GA-MAS algorithm.**GA-MAS,** genetic algorithm multi-agent system.

Their descendants are

$$S1 = P1 + rand \cdot (n_p - m_p) \tag{12}$$

$$S2 = P2 + (1 - rand)(n_p - m_p) \tag{13}$$

Among them, a *rand* is a random number in [0,1]. According to the equations, the population obtained after Pareto's optimal operation is crossed with the crossover probability pc according to Eqs (12) and (13). The pros and cons of the offspring individuals obtained after the crossover are compared with their parents. If the child is better than the parent, the child is retained; otherwise, it retains the parent.

#### 3.2.3 Death and regeneration operations

If the distance between the two points of the Agent corresponds to the distance of the objective function, let one of the agents die. Then a new agent is randomly generated in the domain to replace it. If an agent's performance is worse than other agents in its neighbourhood, one will be randomly selected from the solution after Pareto's selection.

## 4 A comprehensive management system for energy-saving and consumption-reducing distribution network based on GA-MAS

According to the multi-agent hierarchical distributed system theory, the structural diagram of the integrated management system for energy saving and consumption reduction of a distribution network based on a multi-agent setup is shown in Figure 3. The system includes two levels of multi-agents and management layers on the high-pressure side and low-pressure side.

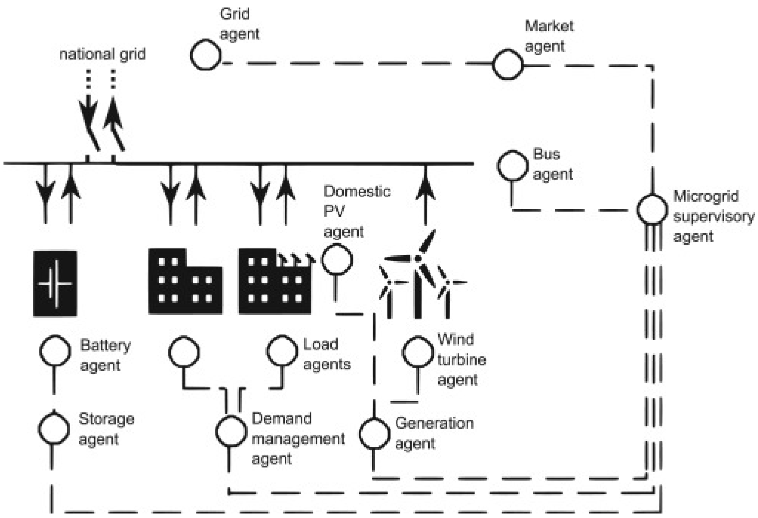


**Fig. 3** Structural diagram of the integrated management system for energy saving and consumption reduction of a distribution network based on multi-agents.
**PV, xxx.**

The interaction and coordination of each Agent on the high-/low-voltage side are completed by the task coordination agent, and the task coordination agents can communicate with each other. Each Agent is connected to the management layer through the task decomposition agent, enabling different agents to connect to the corresponding management layer systems [10]. The various systems of the management layer are connected through the communication and interaction between the agents to realise the interconnection, interoperability and mutual coordination of the operating platform. The data of each system of the management layer can be accessed through Transmission Control Protocol/Internet Protocol (TCP/IP) protocol to achieve the purpose of data sharing and exchange. As a result, the various systems in the management layer connect the high-pressure-side multi-agents and the low-pressure-side multi-agents to realise the interaction and collaboration of the high- and low-pressure-side agents. This further realises multi-level energy saving and consumption reduction.

## 5 Simulation analysis

To verify the correctness and feasibility of the above algorithm, we use Pascal language to compile a programme in the Delphi environment to calculate and analyse the Institute of Electrical and Electronics Engineers (IEEE) 14-node system. In the IEEE 14-node system selected in this paper, we assume 14 nodes, six generators, four transformers and six energy-saving devices [11]. The transformer is regarded as an on-load tap-changing transformer, and the adjustment range of the transformer ratio is $1 \pm 1.25\% \times 8$. The gears are divided into 0–16 and 17 gears. We limit the primary adjustment gear position of the transformer to $\pm 2$ gears, and the conversion relationship between the gear position and the actual transformation ratio is $T = 0.9 + n \times 1.25\%$ ($n$ = 0,1, ... ,16). The upper and lower limits of the generator terminal voltage are 0.9–1.1 pu, and the node voltage is limited to 0.95–1.05 pu. In the calculation process, the reference value of active power is 100 MW, and the reference value of reactive power is 100 MWar.

Tables 1 and 2 show the comparison results of energy saving and consumption reduction in distribution networks based on the GA-MAS optimisation algorithm and the particle swarm optimisation (PSO) algorithm. We use optimisation algorithms to solve the number of high- and low-voltage energy-saving equipment investment sets [12]. We find that the total active power loss is the smallest while satisfying the node voltage constraints. Such a control scheme is reasonable and achieves the optimal operation effect of the energy-saving equipment. In terms of node voltage control, generator active power output and voltage maximum and minimum distortion rate, the GA-MAS-based distribution network energy-saving and consumption-reducing system proposed in this paper has shown excellent results. Compared with the PSO algorithm, the GA-MAS optimisation algorithm reduces the total active power loss to 0.135 pu, while the PSO algorithm shows values as high as 0.138 pu. At the same time, the total investment in energy-saving equipment was reduced by two sets.

**Table 1** Comparison results of different optimisation algorithms

| **Compare items** | **PSO** | **GA-MAS** |
|---|---|---|
| Maximum generator active power, pu | 1.998 | 1.972 |
| Minimum generator active power, pu | 0.462 | 0.458 |
| Maximum generator reactive power, pu | 0.245 | 0.102 |
| Minimum generator reactive power, pu | 0.031 | 0.025 |
| Maximum voltage distortion rate THDu, % | 4.02 | 3.63 |
| Minimum voltage distortion rate THDu, % | 2.97 | 2.89 |
| Maximum node voltage, pu | 1.085 | 1.05 |
| Minimum node voltage, pu | 0.989 | 0.952 |

GA-MAS, genetic algorithm multi-agent system; PSO, particle swarm optimisation; pu, xxx; THDu, yyy.

**Table 2** Comparison of active power loss of different optimisation algorithms

| **Optimisation** | **Total active power loss, pu** | **Number of energy-saving equipment invested** |
|---|---|---|
| **PSO** | 0.138 | 5 |
| **GA-MAS** | 0.135 | 3 |

GA-MAS, genetic algorithm multi-agent system; PSO, particle swarm optimisation; pu, xxx.

Figure 4 shows the GA-MAS and PSO iterative curves. It can be seen from the figure that the convergence accuracy and speed of the GA-MAS algorithm are better than those of the PSO algorithm. In terms of algorithm calculation speed, the time optimised by GA-MAS and PSO is 16.3 s and 34.5 s, respectively. It can be seen that the calculation speed and convergence of GA-MAS are better than those of the PSO algorithm.

## 6 Engineering application

An enterprise's power distribution network has one 110 kV substation, one self-provided thermal power plant and two 10 kV distribution substations. Among them are two sets of 25,000 kVA capacity 110 $\pm$ 8 $\times$ 1.25% on-load tapping transformers and two 110 kV lines. The distribution network was introduced from different substations to supply power to the plant. There were four on-load tapping transformers with a capacity of 6,300 kVA of 10 $\pm$ 8 $\times$ 1.25%, 143 circuits of 10 kV feeders, 256 circuits of 6 kV feeders and two generators sets of 6300 kVA. The system is connected to 16 sets of various types of high- and low-voltage energy-saving equipment. The energy-saving and consumption-reducing management system of distribution networks based

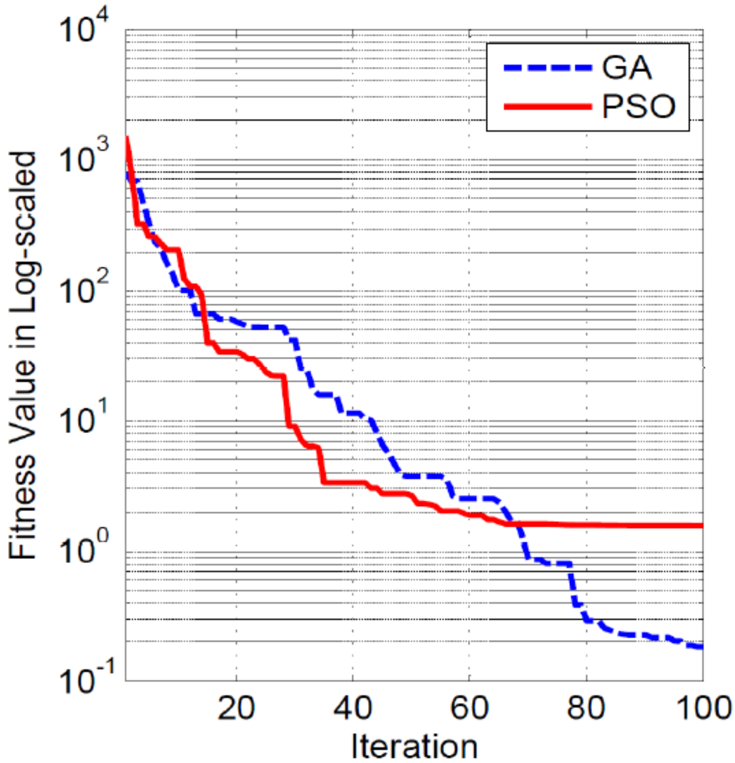


**Fig. 4** GA-MAS and PSO algorithm iteration curve.
GA-MAS, genetic algorithm multi-agent system; PSO, particle swarm optimisation.

on the GA-MAS proposed in this paper has been successfully applied to the enterprise distribution network. The energy-saving and consumption-reducing benefits produced by the system are as follows:

1) Reduction in the number of actions of the tap switch of the on-load tapping transformer: The transformer taps are reduced from 3.87 times per week before the system mentioned in this article is put into operation to 2.08 times per week per unit currently. The number of actions has been reduced by 46%. The investment in the system increases the service life of the equipment and reduces the labour intensity of maintenance.

2) Improvement in voltage quality: Figure 5 shows the voltage curve at the hour of the 110 kV node. It can be seen that the voltage of each node is significantly improved after using the integrated energy-saving and consumption-reducing system of the distribution network proposed in this paper. According to statistics, the qualification rate of busbar voltages >6 kV in the regional power grid within 3 months after the system was connected to operation was 99.96%.

## 7 Conclusion

This paper proposes an integrated management system for energy saving and consumption reduction in distribution networks based on a multi-agent genetic optimisation algorithm. The system uses the GA-MAS algorithm to obtain the best adjustment strength of each energy-saving equipment by comprehensively considering the factors that cause power loss in the distribution network. This enables the energy-saving equipment to obtain the maximum energy-saving benefit with the minimum adjustment cost. The GA-MAS algorithm constructs a MAS environment. Each Agent is equivalent to an individual in the GA. They interact with their domain in this environment. Combined with the evolution mechanism system of the GA, it can quickly and accurately converge to the optimal global solution. A specific calculation example shows that the management system proposed in this paper can reduce the total active power loss and the total number of capacitor input groups. At the

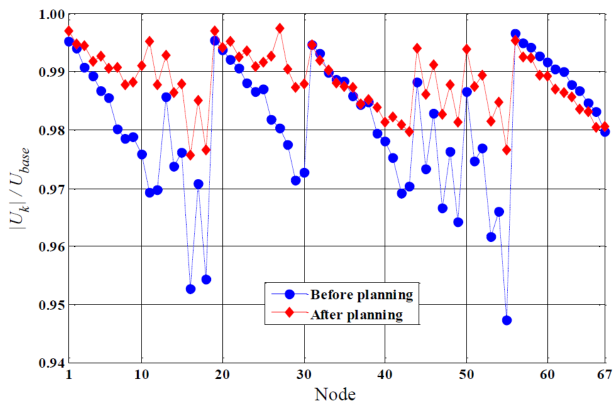


**Fig. 5** Comparison curve before and after node voltage optimisation.

same time, it shows that the GA-MAS algorithm has good calculation efficiency and convergence stability. The integrated management system for energy-saving and consumption reduction of distribution networks based on the GA-MAS algorithm proposed in this paper is of great significance to realising comprehensive energy-saving and consumption reduction of the distribution network in a comprehensive and multi-faceted manner.

## References

[1] Yani, A., Junaidi, J., Irwanto, M., & Haziah, A. H. Optimum reactive power to improve power factor in industry using genetic algorithm. Indonesian Journal of Electrical Engineering and Computer Science., 2019; 14(2): 751-757

[2] Wu, X., Wang, D., Cao, W., & Ding, M. A genetic-algorithm support vector machine and DS evidence theory based fault diagnostic model for transmission line. IEEE Transactions on Power Systems., 2019; 34(6): 4186-4194

[3] Wang, W., Lou, B., Li, X., Lou, X., Jin, N., & Yan, K. Intelligent maintenance frameworks of large-scale grid using genetic algorithm and k-mediods clustering methods. World Wide Web., 2020; 23(2): 1177-1195

[4] Abdalla, A. N., Nazir, M. S., Jiang, M., Kadhem, A. A., Wahab, N. I. A., Cao, S., & Ji, R. Metaheuristic searching genetic algorithm based reliability assessment of hybrid power generation system. Energy Exploration & Exploitation., 2021; 39(1): 488-501

[5] Baroudi, U., Bin-Yahya, M., Alshammari, M., & Yaqoub, U. Ticket-based QoS routing optimization using genetic algorithm for WSN applications in smart grid. Journal of Ambient Intelligence and Humanized Computing., 2019; 10(4): 1325-1338

[6] Moradnouri, A., Vakilian, M., Hekmati, A., & Fardmanesh, M. Optimal design of flux diverter using genetic algorithm for axial short circuit force reduction in HTS transformers. IEEE Transactions on Applied Superconductivity., 2019; 30(1): 1-8

[7] Zarei, B., & Meybodi, M. R. Detecting community structure in complex networks using genetic algorithm based on object migrating automata. Computational Intelligence., 2020; 36(2): 824-860

[8] Iglesias Martínez, M., Antonino-Daviu, J., de Córdoba, P. & Conejero, J. Higher-Order Spectral Analysis of Stray Flux Signals for Faults Detection in Induction Motors. Applied Mathematics and Nonlinear Sciences., 2020; 5(2): 1-14

[9] Hassan, S., Reddy, M. & Rout, R. Dynamics of the Modified n-Degree Lorenz System. Applied Mathematics and Nonlinear Sciences., 2019; 4(2): 315-330

[10] Rezaei, N., Uddin, M. N., Amin, I. K., Othman, M. L., & Marsadek, M. Genetic algorithm-based optimization of overcurrent relay coordination for improved protection of DFIG operated wind farms. IEEE Transactions on Industry Applications., 2019; 55(6): 5727-5736

[11] Mahesh, A., & Sandhu, K. S. A genetic algorithm based improved optimal sizing strategy for solar-wind-battery hybrid system using energy filter algorithm. Frontiers in Energy., 2020; 14(1): 139-151

[12] Mellouk, L., Aaroud, A., Boulmalf, M., Zine-Dine, K., & Benhaddou, D. Development and performance validation of new parallel hybrid cuckoo search–genetic algorithm. Energy Systems., 2020; 11(3): 729-751