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# Distribution network reconfiguration optimization based on genetic algorithm and its influence on operation and maintenance management

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**Abstract:** As one of the advanced application functions of distribution network automation, distribution network reconfiguration is an important optimization means to ensure the normal operation of the power grid. In order to further improve the power supply quality and operation and maintenance efficiency of the distribution network, this paper proposes a reconfiguration method based on improved genetic algorithm, establishes a network topology reconfiguration computational model, and validates the proposed method for the reconfiguration of the distribution network, and the results show that compared with the reconfiguration model of the distribution network constructed by basic genetic algorithm, the algorithm of this paper shows excellent performance in terms of both the comparison of the node voltages and the evolution of the population. The results show that compared with the basic genetic algorithm constructed distribution network reconfiguration model, this paper's algorithm exhibits excellent performance in both node voltage comparison and population evolution, and is capable of realizing optimal power transmission. Finally, the impact of distribution network reconfiguration on operation and maintenance management is analyzed.

**Keywords:** genetic algorithm; distribution network; network reconstruction; fault recovery; infeasible solution

## 1. Introduction

Due to the complexity of distribution network structure, power imbalance will be caused in the case of unreasonable operation structure, which will lead to the increase of line loss, and reduce the operating quality of the system and the reliability of power supply. With the application of distribution network automation, line intelligent circuit breakers and measuring equipment with remote transmission function gradually expand the application, so that the distribution network has the basic automatic operation ability, so that through modern computer technology and control theory, to achieve the change of the distribution network structure, so that the system is in the optimal operating state.

At this stage, the research and application of distribution network reconfiguration can be generally divided into two cases: one is the optimization of network structure under normal operation, and the other is the reconfiguration of power supply restoration under fault conditions. But essentially, the realization principle of the two reconfigurations is to be accomplished by changing the switching state in the distribution network, but the difference lies in the construction of the objective function.

In the research of distribution network reconstruction optimization, Taylor [1] devoted himself to the study of reducing the search space. Through the heuristic

optimal first search strategy, the structures that did not meet the constraint conditions were deleted in the generated solution space. This shows the influence of heuristic rules on the search solution space. The smaller the solution space, the faster the search speed, the larger the solution space, and the longer the search time, the situation of missing the optimal solution will occur, which is not suitable for solving large-scale power grid problems. Grid Network uses Simulated Annealing Algorithms to calculate the network loss of the network state of a large power distribution system. Because the simulated annealing method can choose the objective function at will, the global optimal solution generated will not be affected by the initial solution. For the “dimensional disaster” difficulties existing in most algorithms, the simulated annealing algorithm can also easily solve [2]. However, the difficulty of the simulated annealing method lies in the selection of the scheme. If the scheme is not selected properly, a large number of iterative calculations will be generated, and the generated solution will be opposite to the optimal solution. A researcher proposed the optimal flow pattern method under the prerequisite of the branch delimitation method. The heuristic algorithm of the optimal flow pattern method can be completely detached from the initial node and link structure, and can easily converge to the optimal solution, and its robustness is excellent, which avoids the problem of the branch-and-switch method that relies too much on the initial structure of the nodes and links to a certain extent [3].

In order to obtain an efficient solution method, scholars have optimized and improved a single intelligent algorithm. Chen [4] established a multi-objective reconstruction model with distributed power supply, and used a two-population genetic algorithm based on migration strategy and elite retention to improve the speed and stability of the optimization process. Liang [5] improved the parameter setting in the harmonic search algorithm, redefined the rules of branch disconnection order, and generated a new improved harmonic search algorithm to reconstruct the distribution network. Li [6] combined genetic algorithm and particle swarm algorithm to reconstruct the distribution network, in which the position update rule and coding strategy were improved. Xu [7] improved the explosion operator and termination strategy of the FWA algorithm, and took the loss minimization of the distribution network as the objective function to reconstruct the mining distribution network. Song [8] studied a multi-objective optimization reconstruction model to help solve the multi-objective optimization reconstruction problem of distribution networks containing different types of DG by improving particle swarm optimization algorithm.

It can be seen through the collation of the literature, the existing distribution network reconfiguration methods usually can complete the reconfiguration of the grid, but most of them have problems such as small computational volume, can not guarantee the global optimum, and long solution time, etc. In order to ensure a fast and efficient solution to the grid reconfiguration problem, this paper proposes an optimization method for the reconfiguration of the distribution network with an improved genetic algorithm.

The main innovations of this paper are as follows: starting from the topology of the distribution network, this paper innovatively proposes an improved genetic algorithm based on decimal coding and immuneconcentration operator, and establishes a calculation model for topology reconstruction of the distribution network,

and after the analysis of examples, the optimization model given in this paper is able to carry out effective topology reconstruction of randomly varying distribution network, so as to realize optimal transmission of power, which is of reference for the actual scheduling of the distribution network. The optimization model given in this paper can effectively reconfigure the topology of the distribution network to realize the optimal transmission of electric energy, which has certain reference for the actual scheduling of distribution network [9].

## 2. Improved genetic algorithm

The basic genetic algorithm mainly includes coding, selection, crossover, mutation operation, control parameter selection, iteration termination condition and other specific contents. Because the basic genetic algorithm adopts fixed selection operation parameters, it is easy to form local convergence in the late stage of evolution, the final optimization result is not the optimal result required, which limits its scope of use [10]. In this paper, considering this deficiency, we added the immune mechanism operator, adopted the selection operator based on immune concentration, and adopted vaccine extraction and inoculation to improve the convergence performance in the late stage of population evolution, and provided support for the reconstruction and optimization of distribution network.

The concentration selection method based on vector distance is used to optimize and improve the genetic algorithm. The selection and replication operation according to antibody concentration is the basic principle of concentration selection. Inhibiting the production of high concentration antibody can effectively ensure the good diversity of the population in the late stage of evolution, and avoid falling into the disadvantage of local optimization. In addition, the vector moment method, which is the main method of antibody concentration calculation, can be used to fit the antibody directly to the adaptive function of the optimal solution [11]. It can effectively reduce the search space and further reduce and avoid repeated calculation. The specific flow of applying vector moments to concentration selection operation is as follows:

Give the distance  $L(x_i)$  of antibody  $f(x_i)$  on set  $x$ :

$$L(x_i) = \sum_j^N |f(x_i) - f(x_j)| \quad (1)$$

The  $i$ th antibody concentration  $Density(x_i)$  can be expressed as:

$$Density(x_i) = \frac{l}{L(x_i)} = \frac{l}{\sum_{j=1}^N |f(x_i) - f(x_j)|} \quad (2)$$

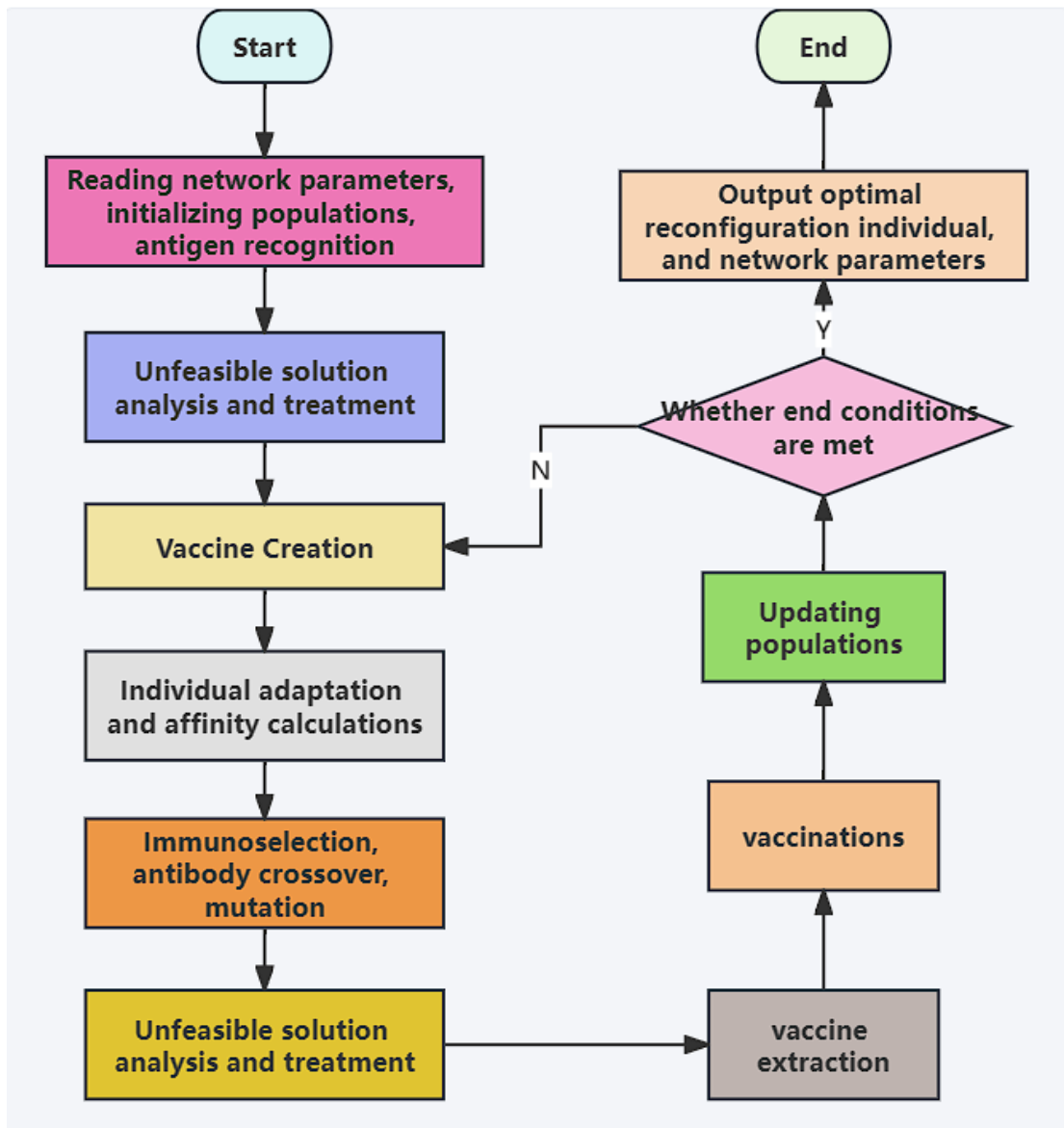
The probabilistic selection formula based on antibody concentration is:

$$P_s(x_i) = \frac{L(x_i)}{\sum_{i=1}^N L(x_i)} = \frac{\sum_{j=1}^N |f(x_i) - f(x_j)|}{\sum_{i=1}^N \sum_{j=1}^N |f(x_i) - f(x_j)|} \quad (3)$$

### 3. Distribution network reconfiguration optimization process based on improved genetic algorithm

#### 3.1. Process framework

The reconfiguration process of the improved genetic algorithm containing immune selection and vaccination proposed in this paper is shown in **Figure 1** below. The improved genetic algorithm has a global search capability and strong robustness to deal with complex distribution network reconfiguration problems. The algorithm adopts a coding method to map the switching states or line configurations in the distribution network as genes on the chromosome, and then guides the genetic algorithm to evolve towards the direction of lowering the network losses, improving the voltage quality and power supply reliability by setting a reasonable fitness function.



**Figure 1.** Reconstruction process of improved genetic algorithm.

For the consideration of economic factors in the actual urban distribution network operation process, this paper chooses to use the reconfiguration model based on line loss minimization when actually carrying out distribution network reconfiguration [12].

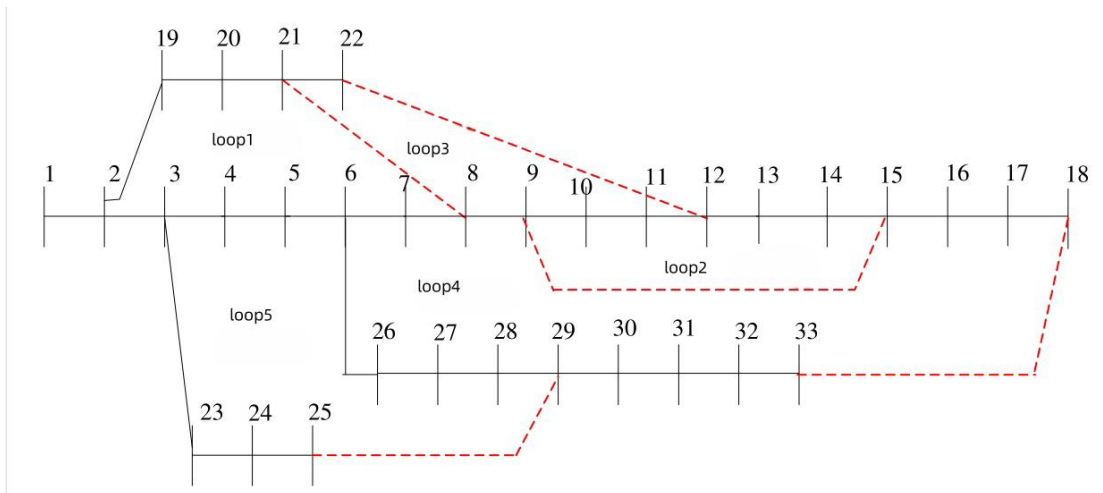
$$\min P_{loss} = \sum_{i=1}^N k_i r_i \frac{P_i^2 + Q_i^2}{|V_i|^2} \quad (4)$$

The constraints to be met for distribution network reconstruction are as follows:

- (1) Grid constraints: After reconstruction, it is necessary to meet the original radial structure characteristics, that is, to comply with closed-loop design and open-loop operation, and all load nodes are required to be able to supply power reliably, and there can be no isolated load nodes and ring network operation.
- (2) Currents constraints: the grid displayed after the reconfiguration process should be ensured to satisfy the currents balancing system.
- (3) Voltage constraints: for the reconfigured network structure, the load node voltages obtained from the trend analysis results should be within the qualified range [13].
- (4) Operation constraint: the distribution network line after reconstruction should be within the reasonable operating load range, not exceeding 80% of the rated operating load, that is, the line is not allowed to run with heavy load after reconstruction.

### 3.2. Analysis and treatment of infeasible solutions

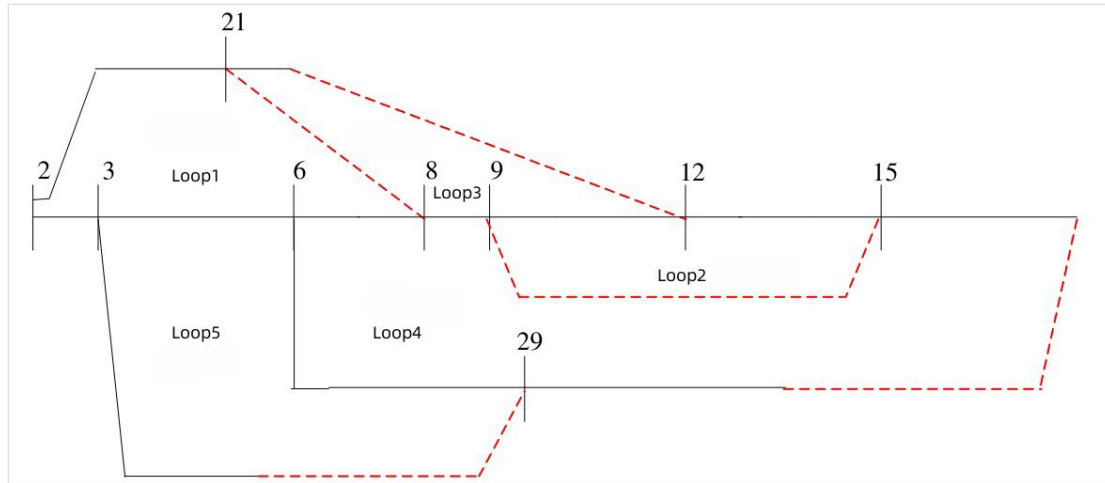
Due to the existence of common switches between circuits, and due to the random initial coding of individuals in the genetic population, some unfeasible solutions will form during immunization, which may lead to islands or self-loops that do not meet the radial power supply structure.



**Figure 2.** IEEE33 node system diagram.

In this paper, the IEEE33-node system is taken as the research object, and the number of feeder lines connected to the node is defined as the “degree”  $D$  of the node, and the node whose  $D$  is greater than or equal to 3 is called the T contact. The IEEE33 node system is shown in **Figure 2** below. Nodes 2, 3, 21, 6, 8, 9, 12, 15, 29 in this

node system are T contacts [14]. The nodes with a degree of 2 are merged. At the same time, the line switches connected to the power point and those not in any loop should be closed. The simplified homeomorphic diagram shown in **Figure 3** will be formed.



**Figure 3.** Simplified homeomorphism diagram.

As can be seen from **Figure 2**, the simplified feeder shunt 2–21 includes four feeder shunt lines such as 20–21, 2–19, 19–20 and 21–22 in the initial structure diagram. The decimal coding reconstruction algorithm adopted in this paper is mainly to form multiple loops by closing all the contact switches first, and then select a switch in the loop one by one to open. The “degree”  $D$  of each node must meet  $D \geq 1$ . When a feeder switch is selected to open, the “degree”  $D$  of the nodes at both ends of the feeder line is reduced by 1. Corresponding to simplified homeomorphism **Figure 3**, it can be seen that only one sub-branch in each feeder branch can be selected to open [15]. If two or more feeder branches are selected, an island will inevitably be formed. For the solution unit coding in the figure above, the following contents can be carried out:

- (1) Select any feeder switch in loop 1 to open, for example, node 6–29 a feeder switch 26–27, then for the switch selection of loop 4, it can no longer be selected from the feeder switch set in node 6–29, can only be selected from other feeder branches, so similar to complete the selection of other loop switches.
- (2) For the solution generated by the immune operation of a certain gene location in the evolution process, the power supply grid should be scanned first, and the switch should be corresponding to the feeder branch in the simplified isomorphism diagram on the basis of dimension, dimension by dimension. If there are two feeder switches in the simplified feeder branch, it must be an infeasible solution. The dimension switch re-selects a feeder switch from the corresponding loop of the dimension for opening operation, so as to correct the infeasible solution and achieve the purpose.

### 3.3. Fitness function

In order to ensure the reconstruction of distribution network and realize that the voltage of each node is within the qualified range, a penalty function is added as a constraint. By punishing the solution that violates the constraint, the constraint

problem is transformed into an unconstrained problem [16]. At the same time, the adverse situation that the solution that does not meet the voltage constraint conditions is directly excluded and the useful information of the individual is lost is avoided. In order to reflect the degree of performance of each individual in the process of population iterative search, it is stipulated that the fitness function value of excellent individuals should be larger, and the fitness function can be constructed into the following form:

$$F(x) = 1 / \left[ P_{loss} + \beta \sum_{i=1}^n \left( \frac{\Delta U_i}{U_{imax} - U_{imin}} \right) \right] \quad (5)$$

In the formula,  $\beta$  is the penalty factor,  $U_{imin}$  is the minimum voltage,  $U_{imax}$  is the maximum voltage, and  $\Delta U$  is the deviation of the node voltage beyond the limited interval.

This can effectively weaken the chance that the solution violating the voltage constraint will enter the next generation population, rather than directly exclude the operation, which is more in line with the idea of population evolution [17]. It can be seen from the fitness function that the closer the position of an individual is to the global optimal scheme, the larger the fitness function value is, while the smaller the fitness function is, the farther the individual is from the position of the optimal solution.

## 4. Analysis of numerical examples

### 4.1. Object selection

In this paper, the IEEE 33-node system is used as an example into the performance validation of the proposed algorithmic model [18]. The system contains a total of 33 nodes, each representing an element of the power system such as generator, transformer, load, or transmission line, and is an important power system analysis tool mainly used to assess the stability, robustness, and reliability of the power system, and to help designers to understand the operating status and fault conditions of the power system, so as to optimize the design of the system.

### 4.2. Parameter setting

The population size of the improved genetic algorithm is set to 50, the length of individuals using decimal coding is the same as the number of loops in the system, which takes the value of 5, and the maximum number of evolutionary iterations of the genetic operation is 100 [19]. In order to verify the performance of the model, we choose to use the basic genetic algorithm and the improved genetic algorithm for the comparative analysis here, and the parameters of the two algorithms are set to be the same, with the differences being that the improved algorithm increases the vector distance immunization selection and vaccine extraction and inoculation operations.

### 4.3. Result analysis

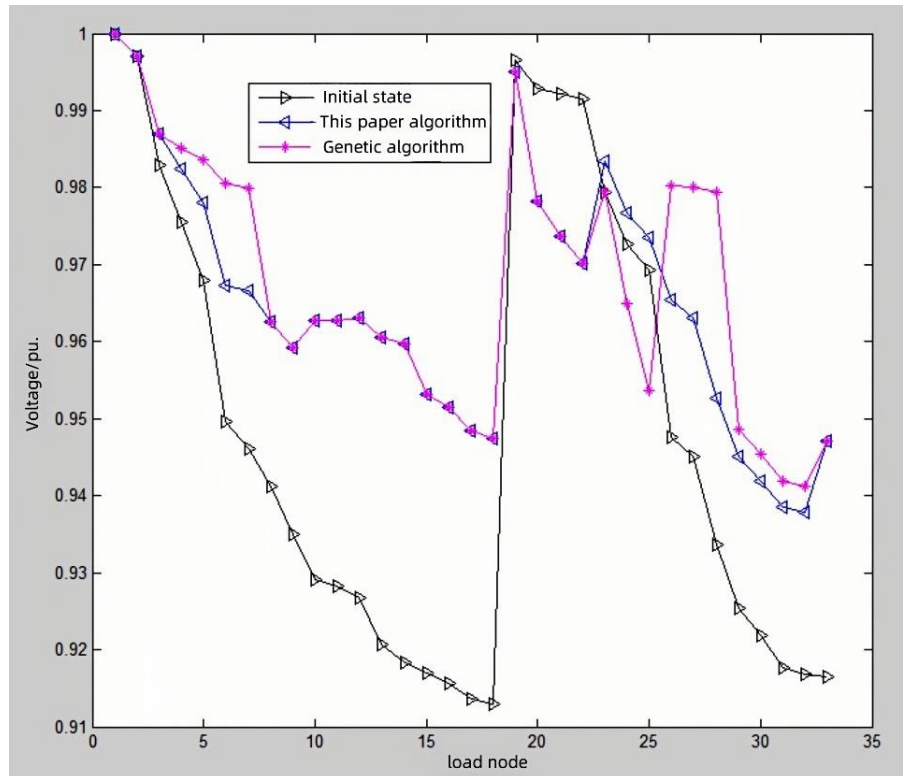
The results before and after reconstruction are shown in **Table 1**. The basic genetic algorithm is used to obtain the local optimal solution. The reconstructed

contact switch sets are 14–15, 7–8, 9–10, 28–29, 32–33, and the system active power loss is 140.003 kW. The global optimal solution can be obtained by using the improved genetic algorithm proposed in this paper. The set of contact switches is 14–15, 7–8, 9–10, 25–29, 32–33, and the system active power loss is 138.974 kW.

**Table 1.** Comparison of reconstructed structures.

	Before Reconstruction	Basic genetic algorithm	Text algorithm
Set of open contact switches	8–21	7–8	7–8
	9–15	14–15	14–15
	12–22	9–10	9–10
	18–33	32–33	32–33
	25–29	28–29	25–29
System active power network loss (kW)	199.98	140.02	138.98
Minimum voltage (pu.)	0.914	0.941	0.938
Lowest voltage node	18	32	32

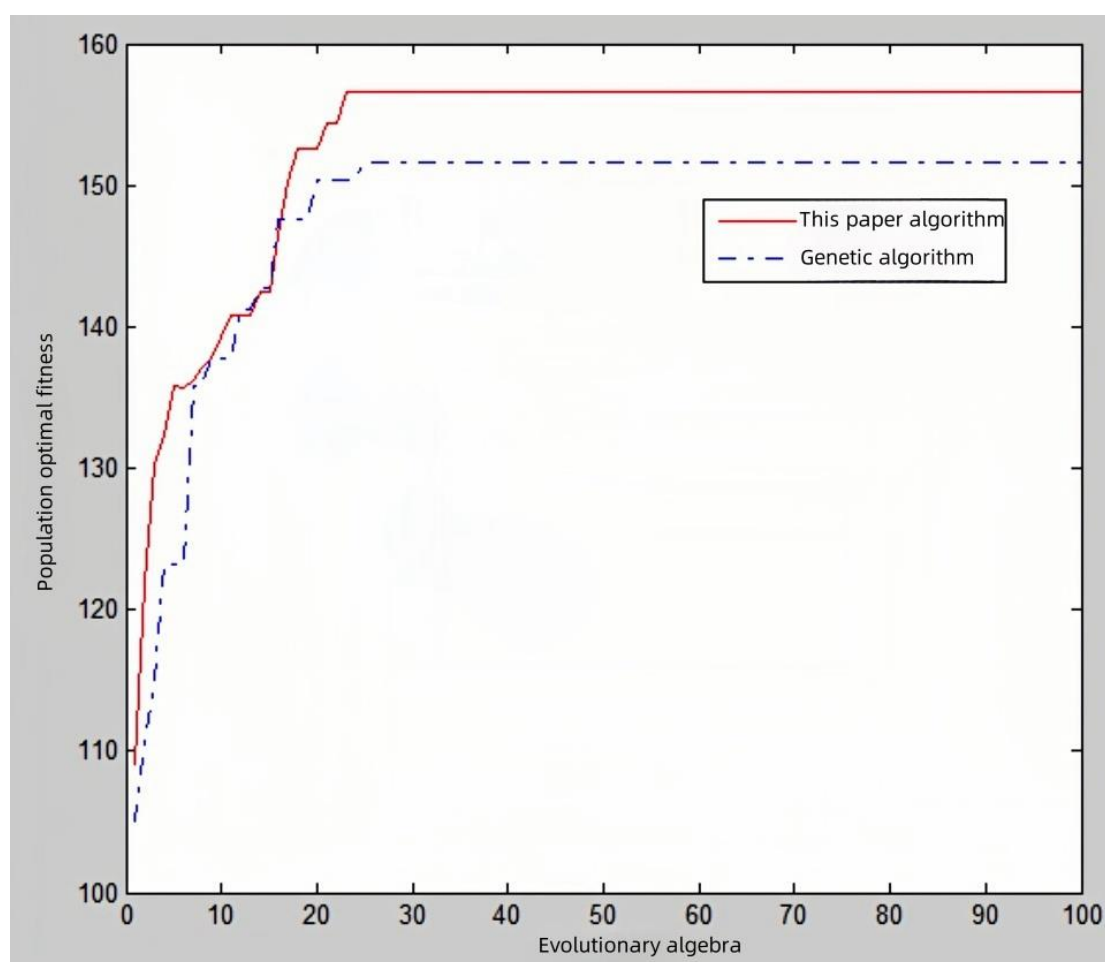
The comparison results of load node voltages before and after the example reconfiguration are shown in **Figure 4** below [20]. From the figure, it can be seen that the reconstruction structure obtained by the two methods are compared with the initial network for the system voltage has a significant increase, but for some of the load nodes, such as nodes 4–7, nodes 26–32 and other segments, the local optimal results of the voltage state is better than the global optimal results, and the reason for this is that the reconstruction of this paper is based on the reconstruction of the system to minimize the loss of due to the requirement for the voltage can be in the limitation of the scope of the requirements.



**Figure 4.** Voltage comparison diagram of load node before and after reconstruction.



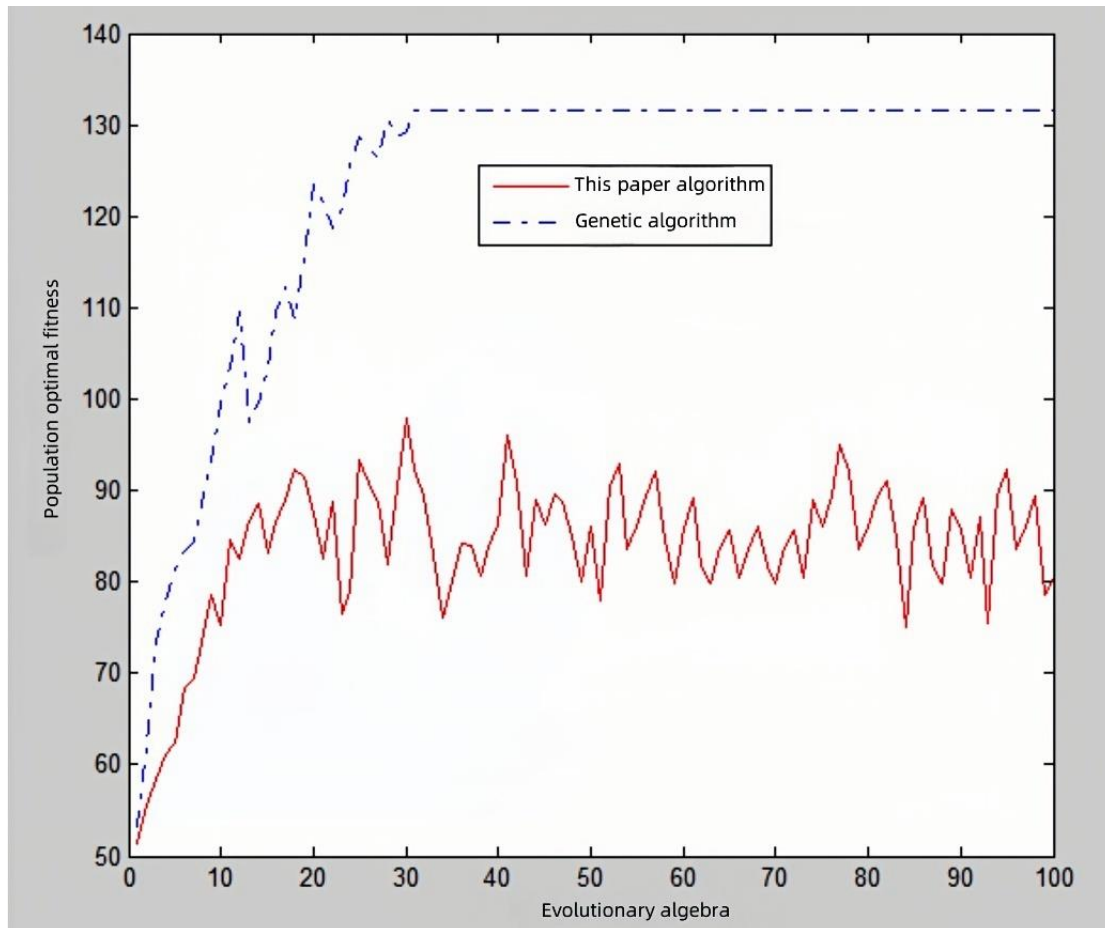
The evolution of the genetic population within 100 generations of the two analysis methods is compared, and the change of the optimal fitness value of the population is shown in **Figure 5** when the results of the analysis are reconstructed by randomly selecting one time. Within 100 generations of evolutionary calculations, the basic genetic algorithm is used to search for the local optimal solution in the 25th generation, and cannot jump out of the local optimal solution [21]. While the algorithm in this paper searches the global optimal solution in the 23rd generation, although in the process of evolution, for the search of the optimal solution of the population, the optimal solution obtained by the algorithm in this paper may have a poorer performance than the optimal solution searched by the basic genetic algorithm with the same number of generations of evolution, but as the number of generations of evolution increases, the algorithm in this paper is able to jump out of the local optimal position effectively to carry out subsequent iterative searches, while the basic genetic algorithm falls into the local optimal position optimal point.



**Figure 5.** Comparison diagram of population evolution.

The comparison of the average fitness values of the population obtained by the reconstruction analysis using two different methods is shown in **Figure 6**. As can be seen from the figure, in the initial evolutionary process, the average fitness values of individuals in the genetic population formed by the two algorithms increased rapidly, and the individuals in the population were able to evolve towards a better result.

However, for the population formed by the basic genetic algorithm, with the increase of evolutionary algebra, the individual diversity in the population is insufficient until the homogeneous population is formed in about 30 generations, which leads to the local optimal position [22]. The improved genetic algorithm, due to the use of vector distance based immune selection operation, can effectively enhance the diversity of the population, and the population keeps a good average trend in the subsequent iterative evolution process.



**Figure 6.** Comparison of average fitness values in the process of population evolution.

## 5. Effect of distribution network reconfiguration optimization on operation and maintenance management

### 5.1. Improve O&M efficiency

Optimization of the distribution network structure can reduce network power losses and the number of unnecessary switching operations. This greatly reduces the workload of operations and maintenance personnel, allowing them to focus on mission-critical and high-value activities [23]. For utilities, reconfiguration of the distribution network results in a reduction in grid operating faults and subsequent O&M costs, allowing them to allocate resources more efficiently, improve overall operational efficiency, and provide financial support for ongoing infrastructure optimization and upgrades.

## **5.2. Improve the reliability of power supply**

Reconfiguration of the distribution network, even in the event of grid faults, is able to achieve rapid adjustment of the power supply path, realizing rapid isolation of faulty areas and rapid restoration of power to non-faulty areas [24]. This process significantly shortens the outage time, reduces the economic losses and social impact caused by power outages, and greatly improves the reliability of power supply. For users, this means a more stable and reliable power supply, which enhances their quality of life and the continuity of their productive activities.

## **5.3. Intelligent operation and maintenance**

As an important part of smart grid construction, the distribution network reconfiguration optimization method provides a decision-making basis for intelligent operation and maintenance. Through the integration of advanced technologies, this method can realize the monitoring and analysis of the operating status of the distribution network [25]. Operation and maintenance personnel can rely on these data and analysis results to formulate more accurate and efficient operation and maintenance strategies, and realize the intelligence, automation and refinement of operation and maintenance work. Promote the development of the power system in the direction of more intelligent, green and sustainable.

## **6. Conclusion**

The network structure of the distribution network has a crucial role in the actual operation status, and the rapid development of the smart grid brings a brand-new opportunity to the development of the power enterprise, and at the same time, it also puts forward higher requirements. In this paper, we first optimize the genetic algorithm, construct the reconfiguration model of distribution network, use the decimal coding method, combined with the characteristics of loop operation, and at the same time, through the processing of infeasible solution of homogeneous embryonic map, which limits the generation of aliased feasible solution. Practical examples are used to verify the performance of this paper, and the results show that compared with the basic genetic algorithm model, this paper's algorithm shows excellent performance both in node voltage for this, and population evolution.

On the whole, the research carried out in this paper has achieved certain research results. However, the research on the reconfiguration of the distribution network in this paper is mainly based on the premise of unchanged operating load, in the process of practical application, the difference of load distribution in different time periods may lead to the reconfiguration strategy of the distribution network needs to be adjusted frequently, and the phased load change is an unavoidable major problem in the regional power grid, so the algorithmic model given in this paper is suitable for this case is to be further verified. The necessity of multi-time dynamic reconfiguration is also high, which will be the main direction of the subsequent research. In this regard, more accurate load forecasting models and algorithms should also be developed in the future research process to predict the load distribution in the future time period in advance and provide data support for dynamic reconfiguration.

**Author contributions:** Conceptualization, JL; methodology, CLZ; software, CLZ; validation, JL; formal analysis, JL; investigation, JL; resources, JL; data curation, JL; writing—original draft preparation, JL; writing—review and editing, JL; visualization, CLZ; supervision, CLZ; project administration, CLZ; funding acquisition, CLZ. All authors have read and agreed to the published version of the manuscript.

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