ARCHIVES OF ELECTRICAL ENGINEERING VOL. 70(2), pp. 307 –323 (2021)

DOI 10.24425/aee.2021.136986

# Application of multi-objective fruit fly optimisation algorithm based on population Manhattan distance in distribution network reconfiguration

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(Received: 12.08.2020, revised: 09.12.2020)

**Abstract:** In order to optimise the operation state of the distribution network in the presence of distributed generation (DG), to reduce network loss, balance load and improve power quality in the distribution system, a multi-objective fruit fly optimisation algorithm based on population Manhattan distance (pmdMOFOA) is presented. Firstly, the global and local exploration abilities of a fruit fly optimisation algorithm (FOA) are balanced by combining population Manhattan distance (*PMD*) and the dynamic step adjustment strategy to solve the problems of its weak local exploration ability and proneness to premature convergence. At the same time, Chebyshev chaotic mapping is introduced during position update of the fruit fly population to improve ability of fruit flies to escape the local optimum and avoid premature convergence. In addition, the external archive selection strategy is introduced to select the best individual in history to save in external archives according to the dominant relationship amongst individuals. The leader selection strategy, external archive update and maintenance strategy are proposed to generate a Pareto optimal solution set iteratively. Lastly, an optimal reconstruction scheme is determined by the fuzzy decision method. Compared with the standard FOA, the average convergence algebra of a pmdMOFOA is reduced by 44.58%. The distribution performance of non-dominated solutions of a pmdMOFOA, MOFOA, NSGA-III and MOPSO on the Pareto front is tested, and the results show that the pmdMOFOA has better diversity. Through the simulation and analysis of a typical IEEE 33-bus system with DG, load balance and voltage offset after reconfiguration are increased by 23.77% and 40.58%, respectively, and network loss is reduced by 57.22%, which verifies the effectiveness and efficiency of the proposed method.

**Key words:** Chebyshev chaotic mapping, distributed generation, distribution network reconfiguration, fuzzy decision method, Pareto optimal, pmdMOFOA, population Manhattan distance

## 1. Introduction

Distribution network reconfiguration, which was firstly proposed by Merlin, is an important means to achieve optimal operation of the distribution network [1]. The topological structure of the network is adjusted by changing the switching state of tie and section switches, which will affect power flow distribution. Ultimately, this condition achieves the purpose of reducing network loss, balancing load and improving power quality [2, 3]. Distribution network reconfiguration can be divided into static reconfiguration based on a certain time point and dynamic reconfiguration based on a certain period of time. In the meantime, the dynamic reconfiguration can be composed of several static reconfigurations according to a time sequence. The content discussed in this paper belongs to the category of static reconfiguration [4].

The problem of distribution network reconfiguration becomes complex due to the influence of DG [5, 6] on distribution network power flow, node voltage, network loss and many other aspects. Some scholars have studied the related problems and achieved certain results [7, 8]. Rao R.S. *et al*. [9] presented a meta heuristic harmony search algorithm (HSA) to solve a network reconfiguration problem in the presence of DG with an objective of minimising real network loss in the distribution system, but the objective function is single, and safety indexes such as voltage offset are not considered. Ling F.H. *et al*. [10] also took minimum network loss as an objective function. This study proposed a broken circle method of an FOA to complete the optimal reconfiguration of the distribution network for solving the problem of the FOA, such as large search space and the need for a large number of infeasible solutions, but the balance between global and local search is not considered in the improvement of the FOA. With the annual increase in DG installation proportion in the distribution network, using an artificial intelligence algorithm to solve the problem of single-objective distribution network reconfiguration can no longer meet the actual needs.

In recent years, the use of artificial intelligence algorithms to optimise the reconstruction of distribution networks has gradually changed from single-objective to multi-objective and has improved the performance indicators of distribution network operation from multiple levels [11]. Sun K.M. *et al*. [12] regarded system line loss, average voltage offset and load balance as multi-objective optimisation problems, and proposed a distribution network topology reconstruction method based on a genetic algorithm (GA), but the geometric mean of the above three objective functions is taken as the objective function of multi-objective optimization, but there are constraints among the objective functions. Ganesh S. *et al*. [13] presented a reconfiguration methodology based on a multi-objective modified flower pollination algorithm (MOMFPA). Minimum network loss, load balance and the voltage profile of the distribution network were taken as objective functions, and the weighted sum method was used to transform a multi-objective optimisation problem into a single-objective optimisation problem. However, the size of a weight factor is easily affected by subjective factors, and the constraint relationship between the objectives is ignored. Thus, the reliability of the optimisation solution needs to be improved.

Chen D.Y. *et al*. [14] proposed a multi-objective static reconfiguration method, adaptive MOPSO based on Pareto optimisation is used to optimise multiple objectives simultaneously, but the convergence and diversity of MOPSO are not illustrated. Li *et al*. [15] studied the reconfiguration of the active distribution network and fully considered its operational risk to improve the practicability and reliability of artificial intelligence algorithms in distribution network reconfiguration. A Pareto multi-objective reconfiguration model, which considers operational economy and operational risk, was established, but the stability of the system is not considered.

Based on the study of an intelligent algorithm in distribution network reconfiguration, this paper proposes a multi-objective reconfiguration method based on a pmdMOFOA, which is used to optimise the performance indicators of distribution network operation. By comparing the convergence and diversity of a pmdMOFOA with other three multi-objective algorithms, the superiority of the pmdMOFOA is proved. The specific arrangement of the paper is as follows: Section 2 describes the objective function and constraints of distribution network reconfiguration, while Section 3 describes the specific improvement strategy of the pmdMOFOA. Section 4 introduces the application of the pmdMOFOA in distribution network reconfiguration, and Section 5 introduces the simulation results and analysis. Finally, Section 6 summarizes the article and shows the next work.

## 2. Multi-objective optimisation model

### 2.1. Objective function

1. Network loss

$$\min f_1 = \sum_{i=1}^{M} \frac{P_i^2 + Q_i^2}{V_i^2} r_i s_i , \tag{1}$$

where: $M$ represents the total number of branches in the distribution network, $r_i/\Omega$ represents the resistance of the branch $i$, $s_i$ represents the state quantity of the branch $i$ ($s_i = 0$, when the branches are broken, and $s_i = 1$, when the branches are closed), $P_i$/kW represents the active power flowing through end of the branch $i$, $Q_i$/kvar represents the reactive power flowing through the ends of the branch $i$, and $V_i$/kV represents the node voltage at the end of the branch $i$. The small $f_1$ corresponds to a better economy.

2. Load balance

$$\min f_2 = \sum_{i=1}^{M_C} \left( \frac{I_i}{I_{i\,\max}} \right)^2 , \tag{2}$$

where: $M_C$ represents the total number of all closed branches of the system, $I_i$/A represents the current flowing through the branch $i$ and $I_{i\,\max}$/A represents the maximum allowable current flowing through the branch $i$. A small load balance indicates better system stability.

3. Voltage offset

$$\min f_3 = \sum_{i=1}^{M_B} \frac{(V_{i,B} - V_{i,BN})^2}{V_{i,BN}^2} , \tag{3}$$

where: $M_B$ represents the total number of nodes in the system, $V_{i,B}$/kV represents the actual voltage of the node $i$, and $V_{i,BN}$/kV represents the rated voltage of the node $i$. The small $f_3$ means the longer service life of the line equipment.

### 2.2. Constraint condition

After the objective function is established, the following constraints should be met in the process of distribution network reconfiguration.

1. Equality constraint

   In the process of distribution network reconfiguration, DG is equivalent to 'negative' load and uniformly transformed into a PQ node, which is more convenient for calculation [16]. The equality constraints are mainly power flow equation constraints:

$$\begin{cases} \Delta P = P_{Gi} - V_i \sum\limits_{j \in i} V_j \left( G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij} \right) = 0 \\ \Delta Q = Q_{Gi} - V_i \sum\limits_{j \in i} V_j \left( G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij} \right) = 0 \end{cases}, \tag{4}$$

   where: $P_{Gi}$/kW and $Q_{Gi}$/kvar, represent the active power and reactive power of DG inflow in the node $i$, respectively, $V_i$/kV represents the maximum voltage amplitude of the node $i$. $G_{ij}/(^\circ)$, $B_{ij}/(^\circ)$ and $\theta_{ij}/(^\circ)$, are the conductance, susceptance and voltage phase difference between two nodes $i$ and $j$, respectively.

2. Inequality constraint

$$V_{i,B\_\min} \leq V_{i,B} \leq V_{i,B\_\max}, \tag{5}$$

$$|I_i| \leq I_{i,\max}, \tag{6}$$

$$g_k \in G, \tag{7}$$

   where: $V_{i,B\_\min}$/kV represents the lower voltage limit of the node $i$, $V_{i,B\_\max}$/kV represents the upper voltage limit of the node $i$, which can ensure the voltage of all nodes within the allowable range, $g_k$ represents the reconstructed network structure, $G$ represents all the network topology sets meeting the radial requirements.

## 3. Multi-objective fruit fly optimisation algorithm based on population Manhattan distance

In this study, *PMD* [17] is used to detect the state of population diversity for reflecting the evolution of the algorithm. The evolution state is divided into two stages of exploration and convergence. The step update mode of different strategies is used to balance the global and local exploration abilities of the algorithm for balancing convergence and diversity performance of the algorithm. A location updating strategy based on Chebyshev chaotic mapping is proposed, which endows the fruit fly population with the ability to escape from the local optimum and effectively avoids the premature phenomenon. A pmdMOFOA selects the best individual history to store in the external archives according to a dominant relationship amongst individuals through the external archive selection strategy. This algorithm also introduced the leader selection strategy, external archive update and maintenance strategy to generate a Pareto optimal solution set iteratively.

### 3.1. Defining population Manhattan distance

*PMD* is defined as the average of minimum Manhattan distance ($MD$) between each fruit fly and other flies in population. $MD$ between fruit flies can be calculated by Equation (8):

$$MD = d_{ij} = \sum_{h=1}^{dim} \left| x_{ih} - x_{jh} \right|, \tag{8}$$

where *dim* is the dimension and $d_{ij}$ is the $MD$ between the $i$-th fruit fly and the $j$-th fruit fly. Minimum $MD$ ($\min(MD)$) between each fruit fly and other flies is obtained by sequencing $MD$, as shown in Formula (9):

$$\text{Sort}\,(MD) \rightarrow \min(MD). \tag{9}$$

The average of $\min(MD)$ is further calculated to obtain *PMD*, as shown in Equation (10):

$$PMD = \overline{\min(MD)}. \tag{10}$$

If the maximum number of iterations is $T$, then the *PMD* of $t-1$ generation can be expressed by $PMD(t-1)$ ($1 \leq t \leq T$). Expression (11) is defined as the set of *PMD* of the first $t-1$ generations:

$$PMD = [1 : (t-1)]\,. \tag{11}$$

Minimum *PMD* in the first $t-2$ generations can be calculated by Equation (12):

$$\min\left(PMD = [1 : (t-2)]\right). \tag{12}$$

### 3.2. Detecting evolution state by PMD

By determining the relationship between the *PMD* of the $t-1$ generation and the minimum *PMD* of the first $t-2$ generations, the evolution state of the population is divided into exploration and convergence stages.

1. If the *PMD* value of the $t-1$ generation is greater than the minimum *PMD* value of the first $t-2$ generations, then the current evolution state is judged as the exploration stage, and population diversity is good. At this time, the $t$ generation population adopts the step update mode with strong local exploration ability to improve the search accuracy.
2. If the *PMD* value of the $t-1$ generation is less than the minimum *PMD* value of the first $t-2$ generation, then current evolution state is judged to be in a convergence stage, and population diversity in the convergence stage is poor. At this time, the $t$ generation population adopts the step update mode with strong global exploration ability to enhance diversity.

By using a corresponding dynamic step adjustment strategy in different stages, the balance between global and local exploration is realized. The convergence and diversity performance of the algorithm are improved.

### 3.3. Dynamic step adjustment strategy

In the standard FOA, the selection of an iteration step directly affects the optimal concentration position, and then affects the convergence speed and accuracy of the algorithm. In this study, a dynamic step factor [18] is introduced to adjust the search step dynamically according to the diverse state of a population, that is, the random search step ($Rand_{value}$) generated by direction and distance is allocated with different step adjustment factors $w(n)$ to realise dynamic adjustment.

$$w(n) = w_0 \cdot \exp\left[-20\,(n/iter_{\max})^a\right], \tag{13}$$

$$Rand_{\text{value}} = w(n) \times (2 \cdot rand - 1), \tag{14}$$

where: $n$ is the number of iterations, $iter_{\max}$ is the maximum number of iterations, $w(n)$ is the dynamic step adjustment factor, $a$ is the adjustment parameter, which is an integer with the value range of 1 to 30 and $rand \in [0,\ 1]$ is the random function. The expression of the random direction and distance of an individual fruit fly searching food by smell is adjusted to

$$\begin{cases} X_i = X + w(n) \times (2 \cdot rand - 1) \\ Y_i = Y + w(n) \times (2 \cdot rand - 1) \end{cases}, \tag{15}$$

where $(X_0, Y_0)$ is the position of the randomly initialised fruit fly population. The dynamic step adjustment factor $w(n)$ is dynamically adjusted according to the real-time evolution state of the population.

### 3.4. Chebyshev chaotic mapping

The heuristic method of uniform distribution randomisation is not ideal for calculating population positions in dealing with complex nonlinear or multi-model problems in an FOA. Marko M. *et al*. investigated the effect of the improved FOA based on ten different chaotic maps, and the experiment shows that the effect of combining with Chebyshev chaotic mapping is best [19]. FOA and chaos theory are combined to improve the ergodicity characteristics of the FOA search process. A chaotic expression alpha = chaos( ) is introduced when updating the position of a fruit fly to ensure the Chebyshev chaotic characteristics of a random fruit fly.

$$X_{i,j} = X_{i,j} + \text{alpha}\left(X_{i,j} - X_{best_{i,j}}\right). \tag{16}$$

### 3.5. External archive selection strategy

For an individual, $I$ is stored in the external archive $Q$ based on a dominant relationship, including the following four situations:

1. If external archive $Q$ is empty, then $I$ will enter directly.
2. If $I$ is dominated by one or some individuals in $Q$, then $I$ will be lost.
3. If $I$ dominates an individual or some individuals in $Q$ and is not dominated by any individual in $Q$, then $I$ will enter and delete the dominated individual in $Q$.
4. If $I$ has no dominant relationship with any individual in $Q$, then $I$ will enter.

### 3.6. Leader selection strategy

The external archives are divided into different levels, and the number of individuals in each level is judged. If only one individual exists, then the individual is directly selected as the leader. If the number of individuals in this level is two or more, then whether the level contains boundary individuals of a non-dominated solution set can be determined. If boundary individuals exist, they are selected as leader individuals, and corresponding numbers of leader individuals are generated according to the number of boundary individuals. Otherwise, the individuals with the largest crowded distance are selected as leader individuals. The number of leaders is uncertain, given that the number of each level division is uncertain.

### 3.7. External archive update and maintenance strategy

When the set maximum capacity of external archives is reached, this study proposed two deletion strategies:

1. The deletion point is located on the last layer level, and the individual of the deletion point level is deleted circularly.
2. The deletion point is not on the last level. All the individuals on the level of the deletion point are directly deleted, and the individuals on the level of the deletion point are deleted circularly.

Circular deletion means that only the individuals with the smallest crowded distance are deleted each time, the crowded distance of the remaining individuals is recalculated, and the external archives are maintained based on the new crowded distance until the given capacity is reached.

## 4. Distribution network reconfiguration process based on pmdMOFOA

The initial population of a feasible solution set is obtained by neighbourhood search before iterative optimization to improve reconstruction efficiency. Then the principle of a pmdMOFOA is used to obtain a candidate scheme set of distribution network reconfiguration. Lastly, the optimal reconfiguration scheme is determined by the fuzzy decision method.

### 4.1. Neighborhood search strategy

When performing a neighbourhood search on one of the loops of the distribution network, the switch states of other loops are kept unchanged. Firstly, the switch which is disconnected in the loop is closed. Then the next switch along the loop direction is turned on under the premise of no generalised isolated node. The abovementioned steps conducted for all switches of all loops, and a feasible solution can be obtained after each operation. The specific steps are as follows.

**Step 1:** Take the current network structure as the starting point of reconstruction, number all loops and select one loop in sequence.

**Step 2:** Take the branch (marked as $K_0$) with the switch off state in the current loop as the starting point, and conduct neighborhood search operation along the loop direction. Close $K_0$, and turn on the switch of the next branch ($K_1$) to judge whether isolated nodes are present in the network. If they exist, then close $K_1$, turn on the switch of the next branch $K_3$ until no isolated nodes exist in the network and output the current network structure to add to the set U.

**Step 3:** Conduct the procedure from step 1 to step 2 for the next loop.

**Step 4:** Perform neighbourhood search from step 1 to step 3 for all loops until the new network structure is the same as the original network structure. Then the neighbourhood search is completed.

In this case, the set U is the set of all feasible solutions satisfying the radial network structure. The set U obtained by neighbourhood search is assigned to the initial fruit fly population, and a Pareto optimal solution set is generated by iterative operation.

### 4.2. Determine optimal reconstruction scheme by fuzzy decision method

After obtaining a Pareto optimal solution set, an optimal solution that meets the requirements of multi-objective, that is, the optimal scheme of distribution network reconfiguration, should be selected. This 'first optimisation, then selection' method not only can ensure that the optimisation process is unaffected by subjective factors, but also can provide reference for decision makers after obtaining the optimisation results. Therefore, the fuzzy decision method based on fuzzy set theory [20] can effectively select the optimal solution. Firstly, to express the satisfaction of the $k-$th solution of the $i-$th optimisation objective in distribution network reconfiguration, the membership function $m_i^k$ is defined as follows:

$$m_i^k = \frac{\left(f_i^{\max} - f_i^k\right)}{\left(f_i^{\max} - f_i^{\min}\right)}, \qquad i = 1, 2, \ldots N_{\text{obj}}, \quad k = 1, 2, \ldots N_{\text{PS}}, \tag{17}$$

where $f_i^{\max}$ and $f_i^{\min}$ represent the maximum and minimum values of the $i$-th objective function, respectively, $f_i^k$ is the $k$-th solution of the $i$-th objective function, $N_{\text{obj}}$ is the number of objective functions, $N_{\text{PS}}$ is the number of solutions in a Pareto optimal solution set. After the membership function of each solution is obtained, the optimal solution $X_k^*$ in a Pareto optimal solution set can be determined according to Equation (18).

$$m^k = \sum_{i=1}^{N_{\text{obj}}} m_i^k \Big/ \left( \sum_{i=1}^{N_{\text{PS}}} \sum_{j=1}^{N_{\text{obj}}} m_i^j \right). \tag{18}$$

Here, Equation (18) represents the satisfaction value of the $k$-th solution. After calculating $N_{\text{PS}}$ satisfaction values and comparing the size, the corresponding solution of $\max\left\{m^k\right\}$ is the optimal solution $X_k^*$.

### 4.3. Distribution network reconfiguration process

The distribution network reconfiguration process is shown in Fig. 1.

**Step 1:** Initialise related parameters, and assign the set U obtained by neighborhood search to the initial fruit fly population.

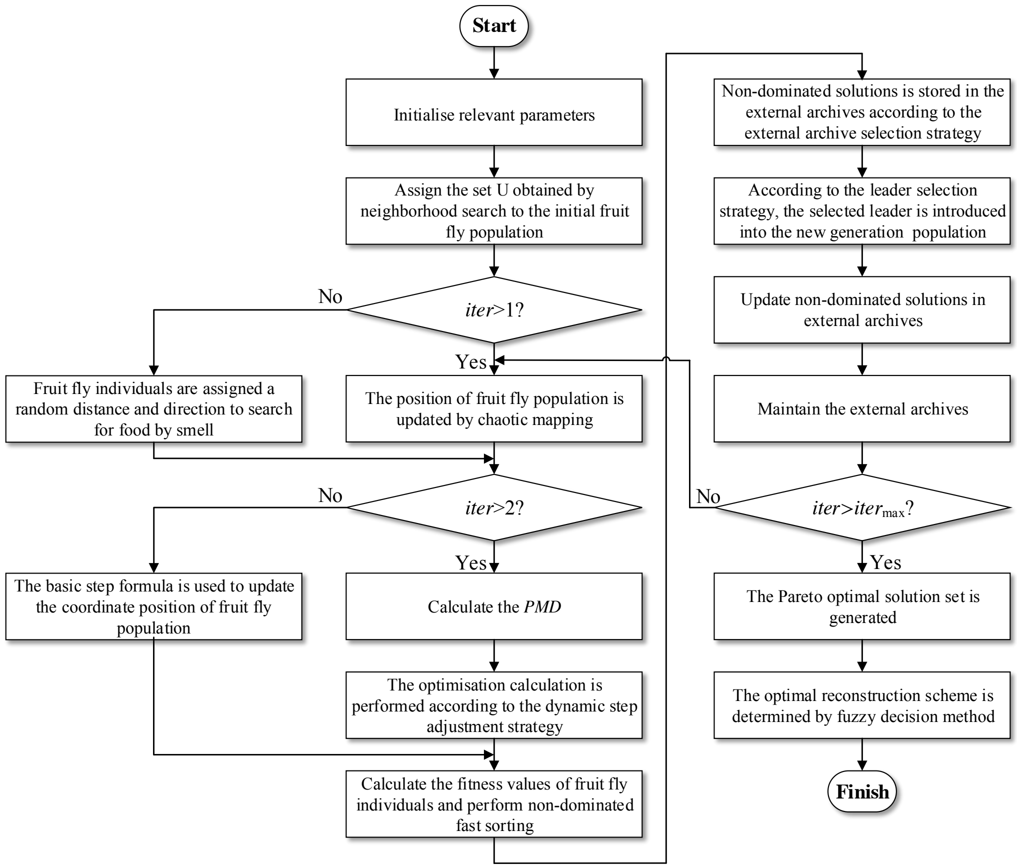


Fig. 1. Flow chart of distribution network reconfiguration

**Step 2:** When $iter = 1$, fruit fly individuals are assigned a random distance and direction to search for food by smell. When $iter > 1$, the position of the fruit fly population is updated by chaotic mapping. Then, it is mixed with the original population again according to a dominant relationship to determine whether to replace a fruit fly of the original population.

**Step 3:** Calculate the $MD$ between all fruit flies in the population, sort them to obtain minimum $MD$ of each fruit fly, and calculate its average, which is the $PMD$.

**Step 4:** When $iter \leq 2$, the basic step formula is used to update the coordinate position of the fruit fly population. When $iter > 2$, the optimisation calculation is performed according to the dynamic step adjustment strategy. The relationship between the $MD$ of the $t-1$ generation population and minimum $PMD$ of the previous $t-2$ generation is judged. If the $MD$ of the $t-1$ generation is greater than minimum $MD$ of the previous $t-2$ generation, then current population diversity is good in the $t$ generation. Thus, the dynamic step update mode with strong local exploitation ability is adopted. Otherwise, current population diversity is poor. Thus, the dynamic step update mode with strong global exploration ability is adopted in the $t$ generation.

**Step 5:** Calculate the fitness values of fruit fly individuals on $N$ objective functions, and perform non-dominated fast sorting of individual fruit fly populations, and according to the external archive selection strategy to judge whether fruit fly individuals enter the external archive.

**Step 6:** According to the leader selection strategy, the selected leader is introduced into the new generation of the fruit fly population.

**Step 7:** Maintain the external archives according to the external archive update and maintenance strategy.

**Step 8:** If the termination condition is not met, then return to step 3. Otherwise, a Pareto optimal solution set is generated, and an optimal reconstruction scheme is determined by the fuzzy decision method.

## 5. Example analysis

### 5.1. Performance verification of pmdMOFOA

In order to compare the convergence performance of the standard FOA and pmdMOFOA, a set population size is 100, the maximum number of iterations is 30, simulation environment is Matlab R2016a, CPU is 3.30 GHz, and memory is 8.00 GB. Convergence algebraic test results obtained by 50 tests are shown in Fig. 2.

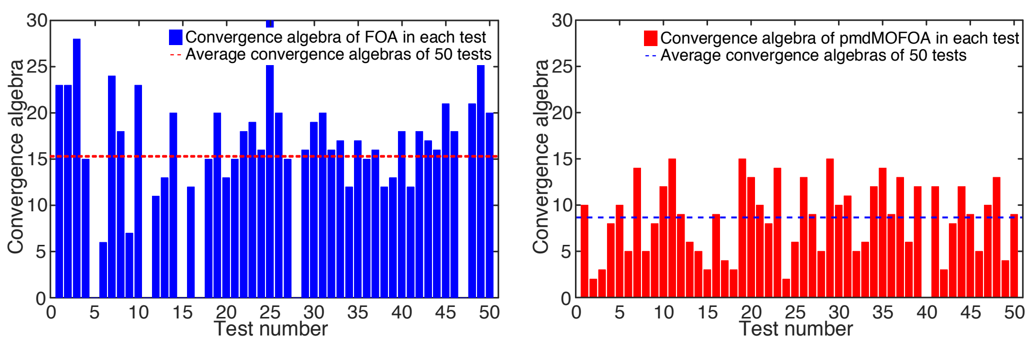


Fig. 2. Test results bar chart for 50 tests

The results show that the average convergence algebras of the two algorithms are 15.30 and 8.48 generations, respectively. Amongst 50 experiments, an FOA does not converge to the optimal value in 30 generations in 6 out of 50 trials. However, a pmdMOFOA only fails once to achieve convergence in the 30-th generation. The average convergence algebra of the pmdMOFOA is 44.58% higher than that of the FOA. Notably, the pmdMOFOA can achieve convergence effect quickly.

To further verify the diversity performance of the pmdMOFOA, a set population size is 100, the maximum number of iterations is 100, and the number of external archives is 50. The distribution performance of the non-dominated solutions of the pmdMOFOA, MOFOA [21], NSGA-III [22] and MOPSO [23] on the Pareto front is tested using the ZDT1, ZDT2, ZDT3, DTLZ1 and DTLZ2 multi-objective test functions proposed in [24]. For the ZDT1~ZDT3 two-objective test function

(Figs. 3–5), most of the two-objective solutions obtained by the four algorithms can find the Pareto front, that is, most of the two-objective solutions can fall on the PF frontier. The results of the pmdMOFOA and MOPSO on the three two-objective test functions all find the Pareto front. By contrast, NSGA-III cannot find the Pareto front on ZDT2. Nevertheless, NSGA-III has good distribution performance on ZDT1 and ZDT3. The two-objective solutions obtained by the pmdMOFOA on ZDT1 and ZDT2 have good distribution on the Pareto front. The distribution performance of the MOFOA on ZDT1 and ZDT2 is good, but the Pareto front is not found in the partial solutions obtained on ZDT3. MOPSO has best distribution performance on the Pareto front of ZDT3, and its distribution performance on ZDT2 is second only to that of the pmdMOFOA.

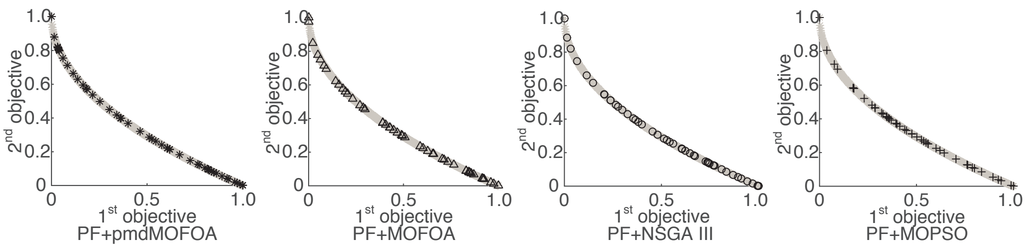


Fig. 3. Non-dominated solutions of each algorithm on the test function ZDT1

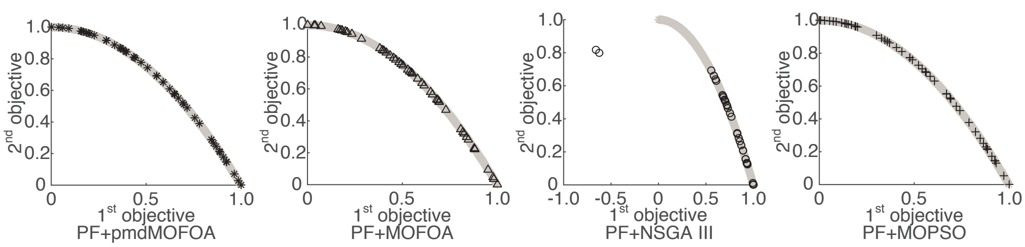


Fig. 4. Non-dominated solutions of each algorithm on the test function ZDT2

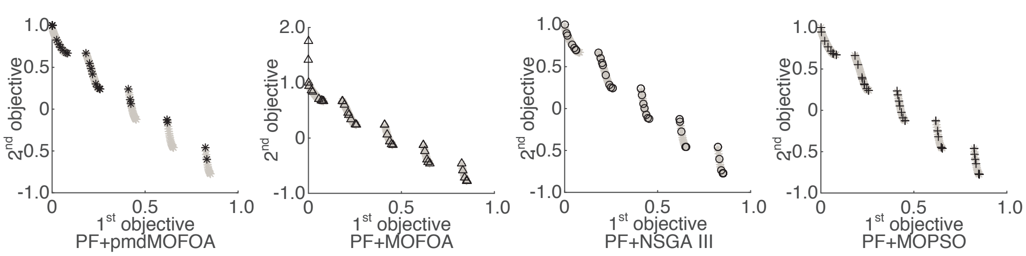


Fig. 5. Non-dominated solutions of each algorithm on the test function ZDT3

For the DTLZ1 and DTLZ2 three-objective test functions (Figs. 6–7), most of the three-objective solutions obtained by MOPSO and the MOFOA are located on the Pareto front surface. The pmdMOFOA finds the optimal Pareto front on DTLZ1 and DTLZ2, and its distribution performance is better than those of other algorithms. However, NSGA-III nearly loses the Pareto front on DTLZ1, and its partial solution lies on the Pareto front of DTLZ2. The abovementioned analysis indicates that the pmdMOFOA not only can obtain good convergence performance but also can ensure good diversity.

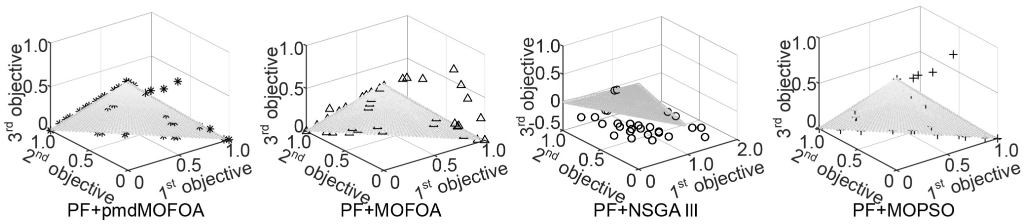


Fig. 6. Non-dominated solutions of each algorithm on the test function DTLZ1

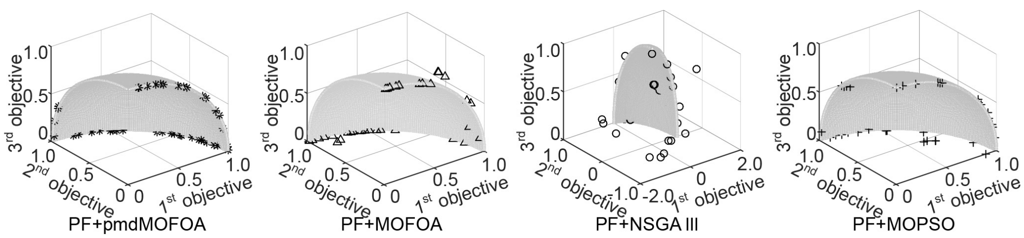


Fig. 7. Non-dominated solutions of each algorithm on the test function DTLZ2

### 5.2. Optimisation results of distribution network reconfiguration

The proposed model and pmdMOFOA are applied to a IEEE 33-bus system, binary numbers 0 and 1 are used to code switches (0 represents open and 1 represents closed). As shown in Fig. 8, the system includes 33 nodes, 37 branches and 5 tie switches. It has a power base line value of 10 MVA, a voltage base line value of 12.66 kV, and a total load of 3715 + $j$2300 kVA [25].

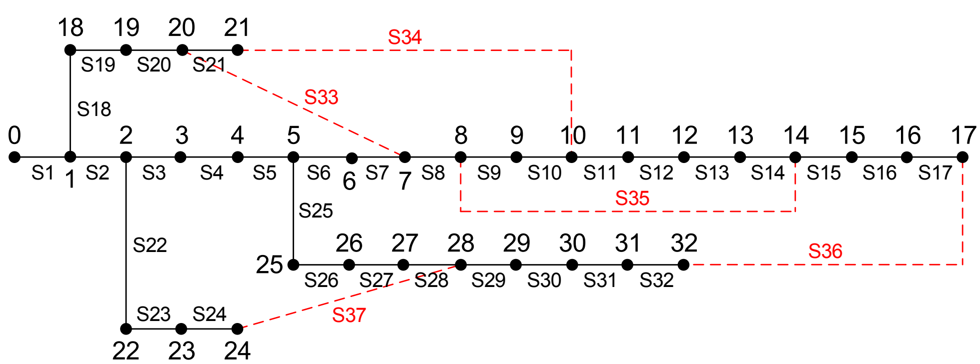


Fig. 8. IEEE 33-bus distribution system

The type of DG connected is fuel cell and photovoltaic power generation equipment, and the access location and capacity are shown in Table 1.

Table 1. Installation and capacity of DG

| DG type | Access location | Capacity/kW | Power factor |
|---|---|---|---|
| Fuel cell | 4, 28 | 80 | 0.8 |
| Photovoltaic | 7, 21 | 100 | 1.0 |

The initial parameters of the algorithm are set as follows: population size is 50, the maximum number of iterations is 100, and the external archive $Q_{\max} = 8$. Firstly, the initial population of the feasible solution set is obtained by neighborhood search. Then, the Pareto front, which is complete and evenly distributed as much as possible, is searched and set as the candidate scheme set of distribution network reconfiguration. Lastly, the optimal reconfiguration scheme is determined by the fuzzy decision method to help power the grid dispatcher complete the decision of the scheme. The pmdMOFOA algorithm is used to solve a reconstruction problem, and a Pareto optimal solution set with DG is obtained as shown in Table 2.

Table 2. Pareto set obtained by pmdMOFOA (DG connected)

| Scheme | Disconnect weitch number | Network loss/kW | Load balance | Voltage offset/p.u. |
|---|---|---|---|---|
| 0 | 33–34–35–36–37 | 206.17 | 2.1125 | 0.0947 |
| 1 | 6–35–34–37–36 | 122.14 | 1.4759 | 0.0557 |
| 2 | 7–35–34–37–36 | 112.37 | 1.5818 | 0.0441 |
| 3 | 33–10–34–37–15 | 95.34 | 1.6244 | 0.0333 |
| 4 | 33–9–14–37–34 | 88.20 | 1.1251 | 0.0331 |
| 5 | 33–10–34–28–15 | 86.19 | 1.1228 | 0.0342 |
| 6 | 33–9–14–28–34 | 85.27 | 1.1040 | 0.0343 |
| 7 | 7–10–14–37–34 | 82.35 | 1.0919 | 0.0355 |
| 8 | 33–9–14–28–15 | 78.98 | 0.9897 | 0.0327 |

The optimal reconstruction scheme with DG after reconstruction can be obtained as scheme 4, as shown in Fig. 9, through the fuzzy decision method in Section 3.2. Similarly, the optimal reconfiguration scheme without DG can be obtained using the abovementioned method. Table 3 shows that network loss and voltage offset after reconfiguration are reduced by 57.22% and 40.58%, respectively, under the condition of DG access. In terms of load balance, the data after reconstruction are increased by 23.77%, and the number of switching operations is four times higher, compared to those of the reconfiguration mode without DG access. Network loss and voltage offset are reduced by 39.51% and 51.18%, respectively, after DG access, load balance is increased by 24.62%, which significantly improves the stability of the system. The number of switching operations is also four times higher.

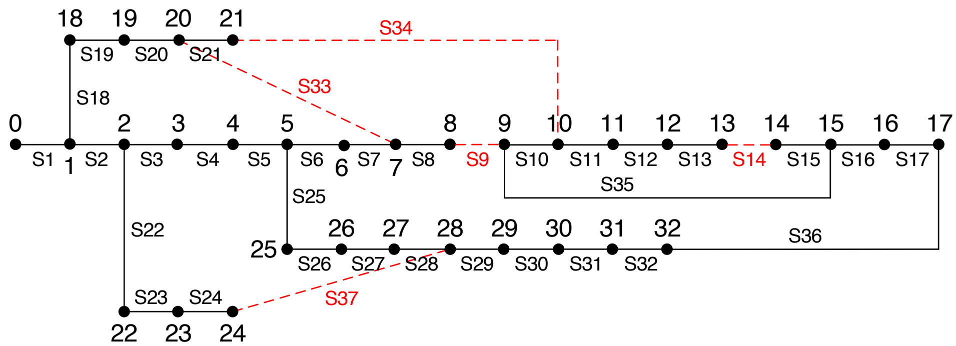


Fig. 9. IEEE 33-bus distribution system after reconfiguration

Table 3. State of network after reconfiguration

| | **DG connected** | **DG not connected** |
|---|---|---|
| **Optimal reconstruction scheme** | 6–11–34–37–36 | 33–9–14–37–34 |
| **Network loss/kW** | 145.81 | 88.20 |
| **Load balance** | 1.4926 | 1.1251 |
| **Voltage offset/p.u.** | 0.0678 | 0.0331 |
| **Switching operation times** | 4 | 4 |

Fig. 10 shows node voltage distribution before and after the reconfiguration of the IEEE 33-bus distribution network. As shown in the figure, the average voltage level of the distribution network with DG before reconstruction is improved compared with that before reconstruction without DG. Moreover, the average voltage level of the distribution network with DG after

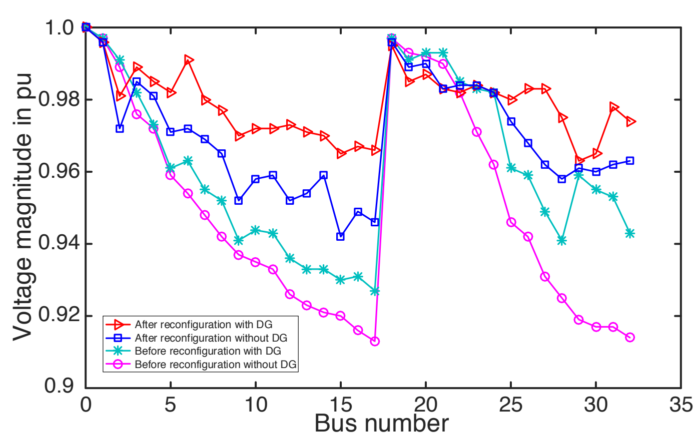


Fig. 10. Voltage distribution for the 33-bus system before and after using the proposed algorithm

reconstruction is further improved than that before reconstruction with DG. Connecting DG to the distribution network and optimizing the network structure not only consume renewable energy but also significantly improve the indicators of the system.

## 6. Conclusion

We proposed an optimisation method for distribution network reconfiguration based on a pmd-MOFOA. After theoretical analysis and set up comparison experiments, the following conclusions were obtained.

1. In reconfiguration of the distribution network with DG, this study proposed a static reconfiguration method of the distribution network based on a pmdMOFOA. This method aims to decrease network loss, achieve load balance and reduce voltage offset. The proposed reconfiguration strategy can optimize the operation state of the distribution network.
2. A pmdMOFOA combined an FOA with PMD to address the problems of weak local exploration ability and proneness to premature convergence of the FOA. The algorithm also introduces the dynamic step adjustment strategy to balance the global and local exploration capabilities. The ability of the fruit fly population to escape from the local optimum is improved because of the location update strategy of Chebyshev chaotic mapping. The premature phenomenon is also avoided effectively.
3. The external archive selection strategy, leader selection strategy, external archive update and maintenance strategy are introduced in the algorithm to ensure the diversity of each solution in a Pareto optimal solution set and improve the practicability and reliability of the distribution network reconfiguration scheme. The optimal reconfiguration scheme is determined by the fuzzy decision method. The simulation results verified the effectiveness and efficiency of the proposed method.

The dynamic reconfiguration of the distribution network is based on the time variation of load and DG, and the dynamic reconfiguration scheme is divided into several interrelated static reconfiguration schemes. This study provided good theoretical guidance for further examining the dynamic reconfiguration of distribution networks.

**Acknowledgements**

This research was supported by the National Natural Science Foundation of China (No. 61663021, 61763025, 61861025), the Provincial Key Research and Development Program of Gansu (18YF1FA058) as well as the Provincial Science and Technology Support Plan Program of Gansu (1304GKCA023).

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