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A Distribution Network Reconfiguration Continuous Method Based on Efficient Solution Space Coding

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Abstract. This paper proposes a distribution network reconfiguration (DNR) continuous method to reduce network loss, balancing load, eliminating overload and improving power quality. When a certain coding rule reduces the dimension and reduces the radius of the variable confidence interval, the first type of non effective solution is avoided in probability through the coding rules and algorithm characteristics, and the second type of non effective solution is completely avoided compared with the expert base, so that the number of power flow calculations is greatly reduced. Through improved Crisscross optimization algorithm (CSO), the directionality is introduced into the horizontal crossing, and the fuzzy clustering idea is adopted to dynamically change the static vertical crossing factor, the simulation results show convergence speed and accuracy are improved, and verify the correctness and effectiveness of the method.

Keywords. Distribution network reconfiguration, crisscross optimization algorithm, network reconfiguration

1. Introduction

The distribution system is an important link at the end of power system, connecting the power supply system or power transmission and transformation system with user facilities, distributing and supplying electric energy to users. Network reconfiguration is not only an important means of distribution system operation and control, but also an important content of distribution management system. The main purpose of network reconfiguration is to change the network structure by changing the state of line switch, reduce the operation loss of the network and meet the constraints of capacity and voltage on the premise of realizing the balance of power supply and demand. With the continuous expansion of distribution network scale, a large number of distribution network reconfiguration methods came into the world [1]. The distribution network reconfiguration realizes the operation mode adjustment by switch the opening and closing states of the two types of switches, it can reduce the network loss and the number of switching actions, eliminate the overload, improved and the economy and reliability of the system operation [2].

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The distribution network reconfiguration problem is actually a combination optimization problem, the number of disconnectors or switches is huge. Therefore, the core of developing distribution network reconfiguration algorithm is to eliminate unnecessary combination search, reduce the amount of calculation, ensure sufficient optimization accuracy, and the optimization result reaches or approaches the optimal solution. At present, the methods used in distribution network reconfiguration mainly include analytical methods, heuristic methods, stochastic optimization methods and so on [3]. The traditional analytical method is not suitable for large-scale distribution system because of its large amount of calculation and slow speed, and most of the reconstruction algorithms are difficult to ensure the global optimal solution [4]. Heuristic methods mainly include branch exchange method (BEM) and optimal power flow (OPF) which can speed up reconstruction [5], but lack of rigorous and feasible mathematical theory to ensure the global optimality of the solution. Stochastic optimization methods include genetic algorithm [6], tabu search algorithm [7], simulated annealing [8], particle swarm optimization [9]. These algorithms have unclear physical meaning and slow convergence speed, but they are suitable for finding the global optimal solution, and more effective methods for solving large-scale nonlinear integer programming problems.

In this paper, the dimensional reduction and compression methods of solution space in distribution network reconfiguration are studied, and the coding method is improved. Firstly, the switching branch range is estimated by the approximate formula of network loss calculation to reduce the dimension and reduce the radius of variable confidence interval. Secondly, the dual population solution space with mapping relationship between continuous variable solution and discrete variable solution is established by combining real number coding and discrete coding. The real solution is mapped to the discrete solution space, and the switching between binary and decimal in the same dimension of the discrete solution is used to skillfully avoid the situation that the same branch set disconnects multiple branches to produce infeasible solutions. At the same time, the direct solution of discrete variables is avoided to reduce the difficulty of solution. Again, the first kind of non effective solutions are avoided in probability through coding rules and algorithm characteristics. Compared with the expert database, the second kind of non effective solution is completely avoided and the number of power flow calculation is reduced. In addition, the horizontal crossing operation and vertical crossing factor of Crisscross optimization algorithm (CSO) [10] are improved to make the optimization effect better.

2. Mathematical Model of Network Reconfiguration

2.1. Economic Restructuring Objective Function

$$\min\mathrm{F} = \sum_{i=1}^{T} k_i r_i \frac{P_i^2 + Q_i^2}{U_i^2} \tag{1}$$

In this formula, T is the number of branches, k_i is the on / off (0 / 1) state of the switch on branch i, r_i is the resistance of branch i, u_i is the terminal node voltage of branch i , p_i and u_i are the injected active and reactive power of node i respectively.

2.2. Power Flow and Network Topology Constraints

The Power flow constraint expression as follow:

$$\mathrm{f}(P_G, Q_{G,} P_{L,} Q_L) = 0 \tag{2}$$

$$g(P_G, Q_G, V, S) \le 0 \tag{3}$$

In this formula, P_G and $Q_{G,}$ is the active and reactive output vector of the power node respectively, P_L and Q_L is the active and reactive power dissipation vector of load node respectively, V is the node voltage vector, S is the branch complex power vector.
The topological constraints expression as follow:

$$grid \in GRID \tag{4}$$

In this formula, grid is the topology of the current network, GRID is a set of all supporting trees, that means a set of network topologies for requirements of acyclic network and no island.

3. Coding Method and Definition of Non Efficient Solution

3.1. Network Simplification and Coding Method

When applying stochastic optimization method to distribution network reconstruction, if the coding method is unreasonable, a large number of infeasible solutions will be generated in the process of initialization and iteration. The following coding rules are adopted in this paper:

- Delete branches and nodes unrelated to the ring network, except power nodes.
- Merge branches with the same effect of unrolling into the same branch set.
- It is defined that each dimension (i.e. a variable) of the solution in the continuous solution space represents a branch set.
- The dimension is the number of estimated branch sets and is encoded by real numbers. It is defined that each dimension (i.e. a variable) of the solution in the discrete solution space represents a branch, the dimension is the number of all equivalent branch sets, and binary and decimal coding methods are adopted. In the first step, binary coding is used to select the estimated branch set. If the dimension is 0, it means that the branch set is not selected, and all branches in the set are closed. If the dimension is 1, it means that the branch set is selected. Note that all dimensions occupied by the set of unmeasured branches are set to zero. In the second step, the branch in the selected branch set is selected by

decimal coding. If the dimension is a positive integer n, it indicates that the nth branch in the branch set is disconnected.

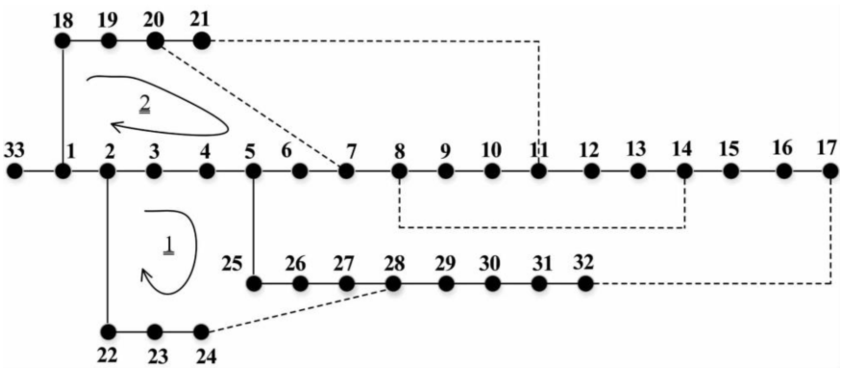


Fig. 1. Single-line diagram of IEEE-33 node distribution system.

As shown in Figure 1, if it is specified that a reconstructed single ring contains only one connecting branch, branches 2-3, 3-4, 4-5, 5-25, 25-26, 26-27, 27-28, 28-24, 24-23, 23-22, 22-2 form a single ring. From the perspective of ring solution, the effect of disconnecting branches 22-2 or 23-22 or 24-22 is the same. Therefore, all branches from node 2 to node 24 are merged into the same branch set and expressed in one dimension in the continuous solution space. If the connecting branches are classified into a branch set, there are only 10 branch sets, which means that the dimension of the solution variable is reduced. Here, the steepness parameter u takes an appropriate fixed value. In order to ensure the radial shape of the network topology, the number of disconnected branches cannot be changed, the five variables with the largest probability value determine that one branch of the branch set is disconnected and set to 1, and the others are set to 0. Then, branch n is randomly selected for the selected branch group in the discrete solution space. It is worth noting that each branch set does not contain all solution ring equivalent branches. This is because the branch exchange range estimated in the previous section determines the alternative branches, which is equivalent to quadratic dimensional reduction in terms of calculation.

3.2. Introduction of Continuity Thought

As the discrete optimization algorithm increases with the combination number, the difficulty of solution increases sharply and the convergence speed is difficult to ensure, this paper does not binarize or decimal the optimization algorithm suitable for continuous variables. The existing continuous method transforms the original discrete problem into a planning problem about continuous variables and then solves it.

For example, in reactive power optimization, the switching group of shunt capacitor and the tap position of transformer are discrete variables, and the generator active and reactive output are continuous quantities. The nearest rounding of multiple discrete quantities is likely to lead to the convergence of the whole solution.

Due to the iterative process of distribution network reconfiguration needs to convert continuous variables into discrete variables for power flow calculation and check constraints, this idea is not applicable. In literature [11], after the above process is similar, it is converted into continuous variables for iteration. In fact, the problem lies in that when the variables in the same solution space are converted from continuous to discrete again, it is easy to fall into the infeasible region, it is difficult to escape, and the population diversity decreases sharply, which is not conducive to the solution of the problem.

In this paper, two mapping relations are established for the solutions of real number coding and discrete coding in Section 3.1, mapping from real number solution to binary solution, and then reflecting the original image integer solution in another mapping relationship. Therefore, the certainty from continuous solution to integer solution is deterministic in random, it is conducive to the application of continuous optimization algorithm to obtain the global optimal solution in the global optimization space containing the whole support tree set of distribution network, effectively reduce the variable dimension and ensure the solution speed.

3.3. Definition of Non Efficient Solution and Effective Avoidance

The constraint test and evolution criterion in network reconfiguration depend on power flow calculation. Due to power flow calculation accounts for the vast majority of the whole running time, if power flow calculation is carried out for each individual of each generation, unnecessary repeated power flow calculation is bound to prolong the convergence time. Therefore, it is necessary to put forward the concept of non effective solution.

Different from the definition of infeasible solution or invalid solution, the noneffective solution is feasible first, that is, it meets the radial shape and does not lose load. This paper defines two types of noneffective solutions: the first type of noneffective solution means that the reconstructed network loss is greater than that before the structure, or the solution generated in this iteration is worse than that generated in a previous iteration on the premise that the network loss value in the optimization process is smaller than the initial network loss, that is, the network loss is greater. The second kind of non efficient solution refers to the same solution generated by the nth iteration and the m ($m < n$) iteration.

Avoiding the first kind of non effective solution can only rely on good coding rules and algorithm characteristics to avoid probability. In fact, the second kind of non effective solution accounts for a large proportion under low dimensional coding, especially in the late stage of iteration, which leads to the extension of convergence time. By establishing an expert database ratio that meets constraints and has no repeated solutions, it is unnecessary to realize multiple repeated power flow calculations to avoid the second kind of non effective solution, then reduce the convergence time and avoid the following ideas:

- Firstly, the initialized real population is obtained in integer form according to the mapping relationship, and the topology constraints before power flow calculation, node voltage constraints after power flow calculation and line capacity constraints are tested. The individuals that do not meet the constraints are regenerated until the discrete population that meets the constraints is formed, the individuals of the discrete population are checked, and a new discrete population without repeated individuals is obtained, and the initial expert database is established.
- The new discrete population satisfying topological constraints generated by each iteration is compared with the expert database. Power flow calculation is

carried out only when the current individual has no record in the expert database.

4. Improved CSO Algorithm and Reconstruction Steps

4.1. Improved CSO Algorithm

CSO algorithm is a random search algorithm based on population. It adopts the double search mechanism of horizontal crossover and vertical crossover. The crossover results spread in the whole population in a chain reaction. This mechanism makes CSO algorithm have obvious advantages in global convergence ability and convergence speed compared with other swarm intelligent optimization algorithms in solving complex optimization problems [12]. The improved CSO algorithm flow chart is as shown in Figure 2:

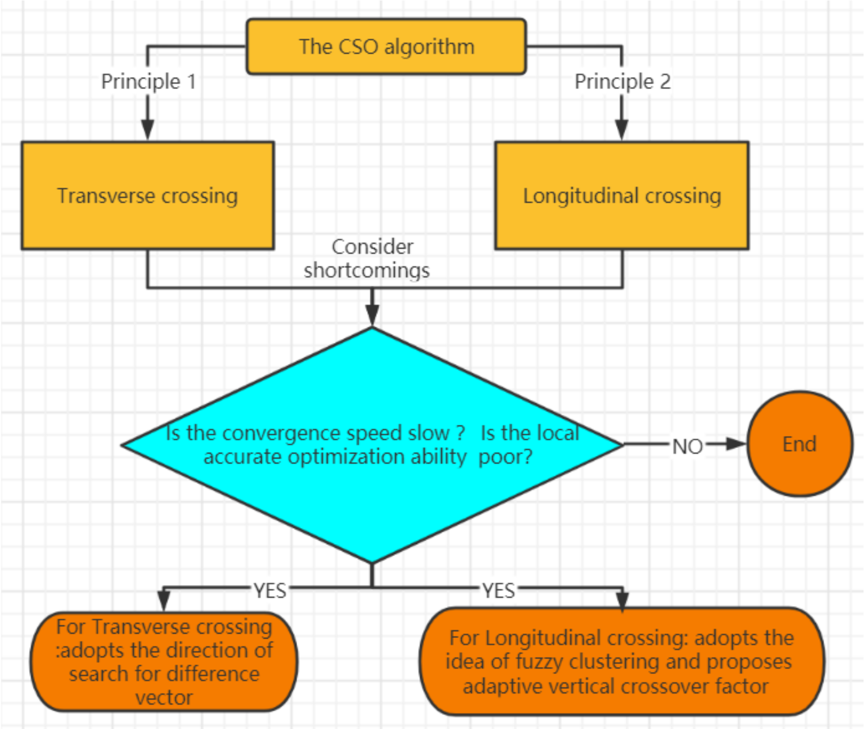


Fig. 2. The improved CSO algorithm flow chart.

The basic principle is as follows:

- Transverse crossing

It is an arithmetic crossing between all dimensions of two different and non repeating individuals selected with a certain probability in the population:

$$M_{hc}(i,d) = r_1 X(i,d) + (1-r_1) X(j,d) + c_1 (X(i,d) - X(j,d)) \tag{5}$$

$$M_{hc}(i,d)=r_2X(i,d)+(1-r_2)X(j,d)+c_2(X(i,d)-X(j,d)) \tag{6}$$

In this formula, i and j represent any two different individuals in the population, d stands for dimension, X and M_{hc} represents parent and child populations respectively, the uniform random number r_1 and $r_2 \in [0,1]$, the uniform random number c_1 and $c_2 \in [-1,1]$.

- Longitudinal crossing

Longitudinal crossing can make the dimension trapped in the local optimum have the opportunity to jump out. Once two different and non repetitive dimensions and are selected, all individuals of the population will make an arithmetic crossing on the dimension:

$$M_{vc}(i,d_1)=r_3X(i,d_1)+(1-r_3)X(i,d_2) \tag{7}$$

In this formula, the uniform random number $r_3 \in [0,1]$.

Due to the optimization only depends on the crossover operation and does not take advantage of the unique properties of the problem, the convergence speed is slow and the local accurate optimization ability is poor. Now, the transverse crossover is improved as follows:

$$X_{con,i}^{k+1} = \omega_i^k (X_{con,b}^k - X_{con,i}^k) + X_{con,i}^k \tag{8}$$

Among that,

$$\omega_i^k = \omega_1 + (\omega_u - \omega_1)\frac{F_b^k - F_i^k}{F_b^k - F_w^k} \tag{9}$$

ω_u and ω_1 are the upper and lower limits of the disturbance factor ω_i^k, F_i^k is the fitness of the i-th individual in the k-th iteration, F_b^k and F_w^k are the fitness of the best and worst individuals in the k-th iteration population, $X_{con,b}^k$ and $X_{con,i}^k$ are the best and i-th individuals in the real coded population respectively.

The improved transverse crossing is no longer a complete random variation, but the base vector searches in the direction of search for $X_{con,b}^k - X_{con,i}^k$ as the difference vector. From the perspective of vector operation, searching in the individual direction with better fitness is conducive to faster convergence to the global optimum.

CSO algorithm vertical crossover factor P_{vc}^k, which directly determines how many dimensions participate in vertical crossover, thus affecting individual self cognitive behavior. If it is fixed according to the standard algorithm, the population information is not fully utilized. Therefore, this paper adopts the idea of fuzzy clustering and proposes P_{vc}^k which changes adaptively with the population information. The equation is as follows:

$$P_{vc}^k = P_{vc\max} + \gamma^k (P_{vc\min} - P_{vc\max}) \tag{10}$$

Among that,

$$\gamma^k = \begin{cases} \dfrac{\sqrt{(F_i^k - \frac{1}{M-1}\sum_{j=1,j\neq i}^{M} F_j^k)^2}}{F_w^k - F_b^k}, F_b^k \neq F_w^k \\ \gamma^{k-1} rand(), F_b^k = F_w^k \end{cases} \tag{11}$$

In this formula, M is the population size, and $rand()$ is the uniform random number distributed in interval [0,1].

4.2. Network Reconstruction Calculation Steps

The calculation of network reconfiguration is divided into the following seven steps:

Step1, read the original data of the distribution system, calculate the initial power flow of the whole network, and obtain the initial network loss and initial node voltage distribution.

Step2, call the subroutine of reduced dimension and compressed variable confidence interval radius to estimate the exchange branch of each ring.

Step3, determine the dimension of variable and constant (set of branches not estimated), as well as the interval number of continuous (real) coded and discrete (integer) coded variables of each variable.

Step4, according to various group dimensions and the mapping relationship between the two populations, the real population is initialized to form the initial discrete population, the power flow distribution of the latter is calculated, and the initial expert database is formed.

Step5, for the real population, the improved horizontal operation is carried out by using equation (8), the discrete population satisfying topological constraints is formed by mapping and reflection, and then compared with the expert database, the power flow calculation and constraint test of some individuals are carried out, the dominant solution is retained by the competition operator, and the expert database is updated.

Step6, for the discrete population after horizontal operation, calculate the P_{vc}^k of this iteration, change the previous crossover operation to vertical crossover, and repeat the subsequent process.

Step7, Judge whether the iteration is over. If yes, output the result. If not, go to step 5.

5. Simulations

The simulation environment is MATLAB R2010b, the basic parameters are population size M_1 =100, M_2 =20, transverse crossing factor P_{hc} = 1, static longitudinal crossing factor P_{vc} = 0.7, upper limit ω_u = 0.7 and lower limit ω_1 = 0.1 of disturbance factor, upper limit $P_{vc\max}$ = 0.8 and lower limit $P_{vc\min}$ = 0.2 of adaptive longitudinal crossing factor, iteration times D_1 = 100, D_2 = 20 and D_3 = 30.

Now, two examples are simulated and analyzed. Example one is the ieee33 bus distribution system [12], with the population size of M_1 and the number of iterations of D_1. Figure 3 shows the node voltage distribution of the system before and after reconstruction. It can be seen that the node voltage distribution is significantly improved after reconstruction. The lowest node voltage is changed from bus 17 to bus 31, and the unit value increases from 0.913 to 0.9378.

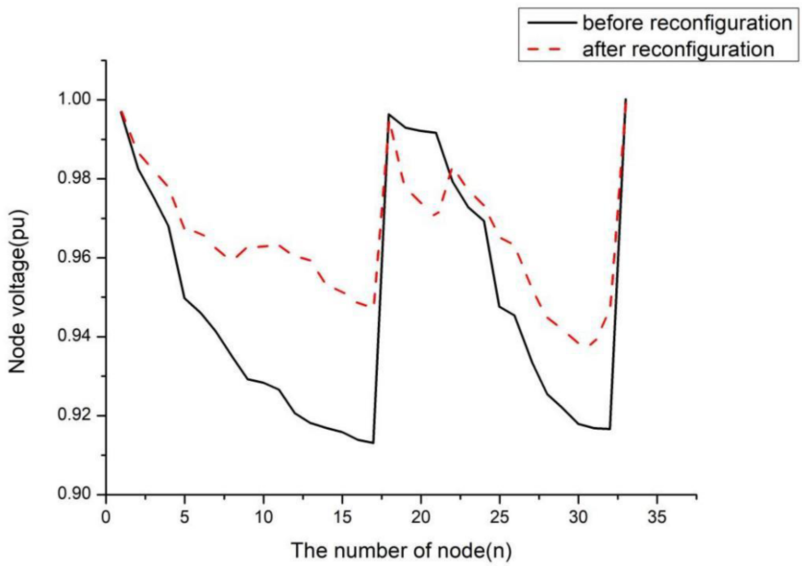


Fig. 3. Voltage profile for IEEE 33 node system before and after reconfiguration.

The Figure 4 shows the optimization convergence curves of different CSO. Dimension Reduction CSO(DRCSO) is the improvement of the standard CSO algorithm after dimensional reduction and interval radius reduction. Self adaption DRCSO(SADRCSO)is improved to adaptive longitudinal crossover on this basis, and Improved SADRCSO(ISADRCSO)is the improved algorithm after considering the non effective solution in this paper. It can be seen that its convergence speed has been significantly improved.

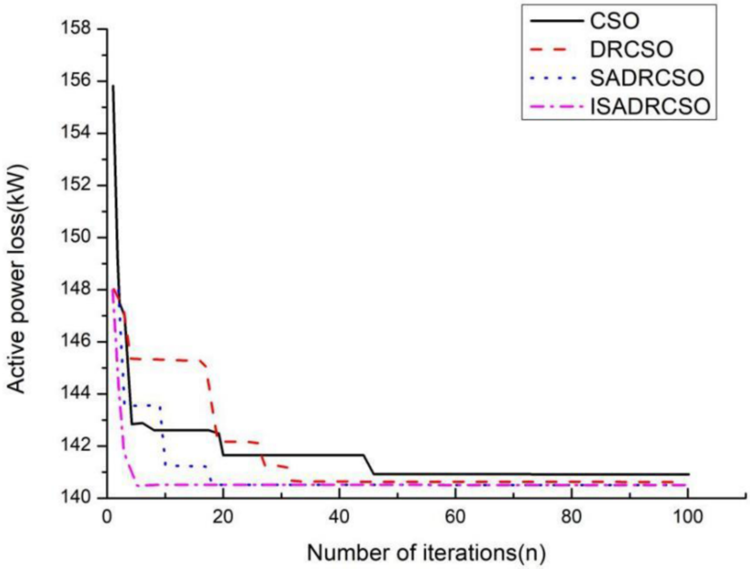


Fig. 4. Convergence curve of different CSO.

The above algorithms converge to the optimal solution under a given number of iterations. The open branches are 6-7, 8-9, 13-14, 24-28 and 31-32, and the network loss decreases from the initial value of 202.68kw to 139.55kw. Table 1 shows the performance comparison of the algorithm. In order to reduce the random error, each algorithm runs 20 times. After DRCSO reduces the dimension and reduces the interval radius, the average convergence time relative to CSO is reduced by 40%. After ISADRCSO considers avoiding the non effective solution, the average convergence time relative to SADRCSO is reduced by 74.9%, and the average number of convergence iterations is only 5 times. Obviously, the convergence speed is faster than that in literature [10], and it converges to the global optimum after 20 consecutive runs, and the robustness is better.

Table 1. Performance comparison among four CSO algorithms.

Name	Average convergence time	Average convergence iterations	Times of convergence to global optimum
CSO	68.361	46	17
DRCSO	46.506	32	20
SADRCSO	26.796	18	19
ISADRCSO	6.724	5	20

The example two is a part of PG &E distribution system, which is a 69 bus system [12]. Figure 5 compares the convergence of ISADRCSO with dimensional reduction and interval radius reduction in population size M_2 and iteration number D_2 with ISADRCSO without prior estimation of branch range operation. It is not difficult to find that ISADRCSO converges globally after 3 iterations, in which the convergence time is 3.585s, while ISACSO needs 10 iterations for local convergence, in which the convergence time is 9.679s.

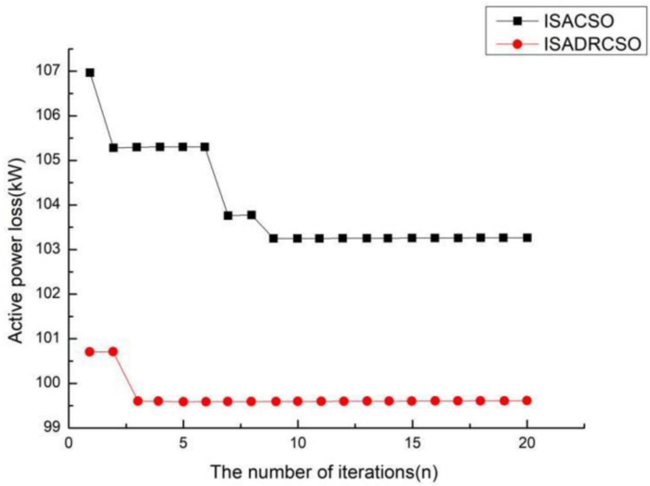
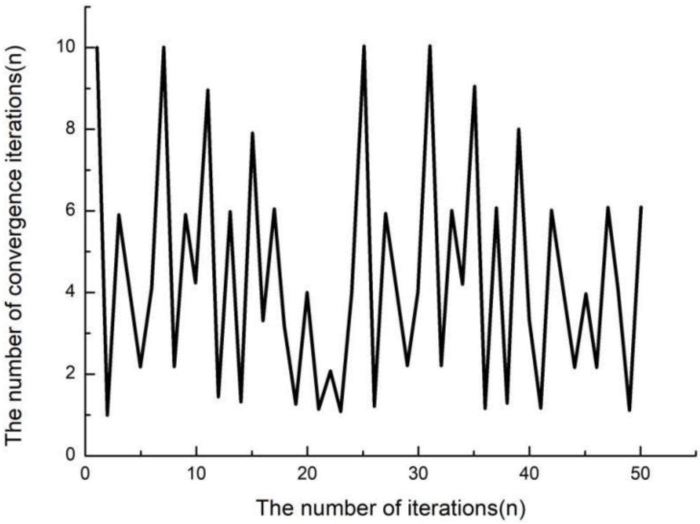


Fig. 5. Convergence curve of two CSO.

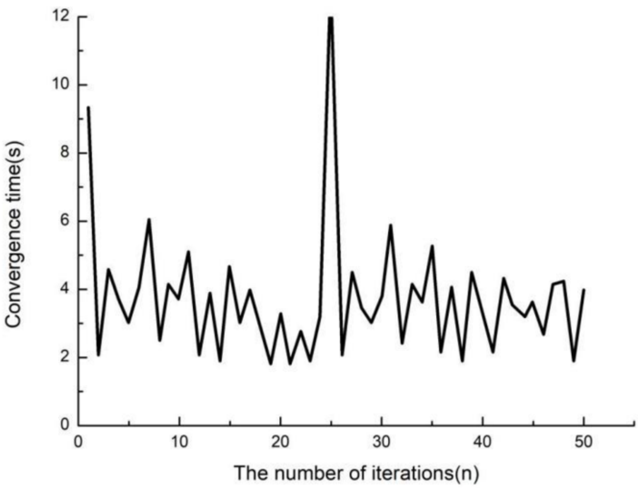
In order to ensure the global convergence of ISACSO, the population size is changed to M_1 and the number of iterations is changed to D_3. However, the robustness is not strong. The global convergence is 14 iterations, in which the convergence time is 80.864s and the minimum network loss is 99.6032kw.

Taking the node number in reference [13] as an example, the reconstruction results of this paper show that the disconnected branches are 10-70, 12-19, 13-14, 46-47 and 50-51. Although other algorithms [14] are different from individual disconnected branches in this paper, the network loss and the lowest node voltage are the same. In essence, nodes 45, 46 and 47 are unloaded, so the effect of disconnecting branches 44-45, 45-46, 46-47 or 47-48 is the same. Therefore, the reconstruction results in this paper are consistent with most other algorithms. Among them, the immune algorithm [14] has an average number of convergence iterations of 34, while the fuzzy genetic algorithm [15] needs 300 iterations to converge when it runs for 50 consecutive times, and the hybrid particle swarm optimization algorithm [16] has an average number of convergence iterations of more than 10 times, with a convergence time of 7.609s. In this paper, it runs for 50 consecutive times, with an average number of convergence iterations of 4.4 times and an average convergence time of 3.781s, Obviously, the convergence speed is significantly improved. However, the broken branches of binary crossbar algorithm [11] are 11-66, 13-20, 12-13, 46-47 and 50-51, which are obviously sub-optimal solutions and are not difficult to verify.

Figure 6 shows the curve of convergence iteration times and convergence time of ISADRCSO running for 50 consecutive times, in which the maximum number of convergence iterations is 10 and only 4 times, and only 3 times run local convergence.



(a)



(b)

Fig. 6. Number of iterations and convergence time of 50 times run.

In this coding method, after branch estimation, the number of search branches is reduced from 57 to 18, the variable dimension and interval radius are greatly reduced, and the convergence speed is further improved after effectively avoiding the non effective solution in the low dimensional solution space. The comparison with other algorithms fully shows the effectiveness of this method.

6. Conclusions

This paper studies the solution space dimensional reduction, compression and coding improvement methods of distribution network reconfiguration, and proposes a continuous optimization algorithm of reconfiguration. Firstly, the approximate formula of network loss calculation based on load current is derived to determine the minimum branch range of the optimal solution, compress the solution space, improve the optimization efficiency, and establish the mapping relationship between continuous variable solution and discrete variable solution. Secondly, a two-population solution space with mapping relationship between continuous variable solution and discrete variable solution is established to avoid directly solving discrete variables and prevent the amount of calculation from increasing exponentially with the increase of the scale of combination optimization problem. This method also has reference significance for exploring how to apply the effective mathematical method and optimization theory suitable for continuous variables to the discrete variable optimization model. Finally, the non effective solution is defined. By relying on the coding rules and algorithm characteristics, the first type of non effective solution is avoided probabilistic, and the second type of non effective solution is completely avoided compared with the expert database. The number of power flow calculation is greatly reduced and the calculation time is shortened.

The CSO simulation example used in this paper shows that the performance of the algorithm is improved by adding the directional guidance of horizontal crossing operation and dynamic vertical crossing factor, and the convergence speed is faster than other algorithms. It is proved that this method can effectively find the global optimal solution, and the calculation speed has obvious advantages.

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