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Distribution Network Reconfiguration Method with Distributed Generators Based on an Improved Shuffled Frog Leaping Algorithm

Xuzhu Dong, Zhengrong Wu, Liming Chen, Zhiwen Liu and Xiaoliang Xu

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Xuzhu DONG, Zhengrong WU, Liming CHEN, Zhiwen LIU
Electric Power Research Institute of China Southern Power Grid
Guangzhou, China
dongxz@csg.cn, wuzr@csg.cn, chenlm2@csg.cn, liuzw2@csg.cn

Xiaoliang XU*
Nanjing NARI-Relays Electric Co.,Ltd
Nanjing, China
1296685433@qq.com

***Abstract*—Reconstruction of a distribution network is a complex nonlinear combinatorial optimization problem. A reconfiguration algorithm of a distribution network based on an improved shuffled frog leaping algorithm using molecular dynamics theory and cloud simulation theory was proposed to solve the problems of slow convergence for current distribution network reconfiguration method. The reconstruction optimization process of the distribution network was as follows. First, the integer coding strategy based on the independent loop was adopted, and the initial data of distribution network was input, followed by random generation of the effective initial swarm of corresponding scale; Second, the distribution network was simplified, and the effective solution was obtained based on the reconfiguration network simplification principle; Third, the back forward sweep algorithm method for was used for the power flow calculation of effective solutions; Finally, iterative swarm optimization was conducted based on the improved shuffled frog leaping algorithm(SFLA). The simulation results based on the IEEE33 node distribution system showed that the active network loss value of the system was decreased obviously, reaching 16.57%. The active power P increased significantly compared with that before the reconfiguration in which the distributed generators (DGs) were accessed. The proposed algorithm has good optimization performance in solving the problem of distribution network reconfiguration compared with the traditional particle swarm optimization (PSO) and the differential evolution algorithm (DE).**

***Index Terms*—Distributed generator, distribution network, reconfiguration algorithm, improved shuffled frog leaping algorithm.**

I. INTRODUCTION

With increased urban development, the performance of a distribution network, such as power quality and power supply reliability, will be adversely affected if a number of distributed generators (DGs) are accessed by the smart grid. In this situation, as an effective method of improving efficiency, power reliability and power supply quality of the distribution network, the research on reconfiguration and operation control of distribution network with DGs plays a critical role in loss reduction, load balance and reactive power optimization. Traditionally, changing the switch state is frequently adopted as a method of distribution network reconstruction to alter the network topology, thus achieving load balance and loss decrease. However, variations in the value and direction of power flow via the access of DGs, such as wind power and solar power, can lead to an increased complexity of distribution network reconfiguration. Active loss reduction[1-2], load equalization and power restoration optimization are currently the most popular technical methods for distribution network reconfiguration, the main objective of which is loss reduction. Regarding optimization algorithms, the differential evolution algorithm[3-4], particle swarm algorithm[5], genetic algorithm[6] and so on[7] have been widely applied. A reconfiguration algorithm of a distribution network based on an improved shuffled frog leaping algorithm is proposed in this paper. Referencing the concept of molecular dynamic simulation[8-9], the algorithm in which the prone-stability and randomness of the cloud model[10] are utilized, effectively balancing the relationship between the swarm diversity and the searching efficiency by adopting a novel updating strategy for the worst individual. The results of the distribution network configuration experiment have indicated that this method has a high convergence rate, powerful global searching ability, and can overcome the problems of local optimization and invalid solutions.

II. MATHEMATICAL MODELS OF DISTRIBUTION NETWORK RECONFIGURATION

Minimization of the network loss is generally chosen as an optimized objective function in the reconfiguration process and can be represented as

$$\min P_{loss} = \sum_{i=1}^{n} k_i r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{1}$$

where P_{loss} is the active loss of system, n is the number of branches, P_i and Q_i are the active power and reactive power, respectively, that flows through branch i, V_i is the node voltage at the terminal of branch i, r_i is the resistance of branch i, and k_i is the state variable of switch i, with 0 indicating open and 1 indicating closed.

Distribution network reconfiguration is subject to the following constraints:

1) Topology constraint, i.e., there is no isolated island, and a ring network exists in the network.

2) Node voltage constraint, i.e., $V_{min} \leq V_i \leq V_{imax}$, where V_i, V_{min}, and V_{imax} are the voltage, the voltage lower limit, and the voltage upper limit of node *i*, respectively.

3) Branch capacity constraint, i.e., the actual power cannot exceed the allowable capacity.

4) Power flow constraint, i.e., the reconfiguration should satisfy the power flow constraint equation.

III. Improved Algorithm of Distribution Network Reconfiguration

A. Coding mode of Distribution Network

To determine the topological structure of the reconstructed network, the switch state in the network is represented using the binary encoding method[11]. The integer encoding strategy based on an independent loop is adopted to reduce the coding dimension and narrow the solution space. The encoding rules are briefly restated as follows:

1) All contact switches should be closed before reconfiguration to form some independent loops. The switches on the branch that are unowned by any loop must be closed while the power grid is running, and such switches should not be considered when coding.

2) The switches connected to a power supply should also be closed, and they should not be considered when coding.

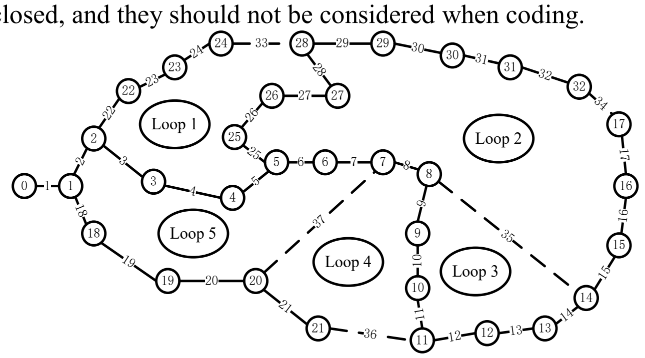

Fig. 1. Example of a figure caption.

TABLE I. Description of the Loop Branches

Loop number	Switch number of loop branch	Maximum number of branch
1	2,3,4,5,22,23,24,25,26,27,28	11
2	5,6,7,8,14,15,16,17,25,26,27,28,29,30,31,32	16
3	8,9,10,11,12,13,14	7
4	7,8,9,10,11,20,21	7
5	1,2,3,4,5,6,7,18,19,20	10

Combined with the simplification strategy above, the coding mode is specified with the example of the IEEE 33 node distribution system illustrated in Fig. 1. As shown in the figure, the contact switches are 33-37. All the contact switches 33-37 denoted with broken lines should be cut before reconfiguration. At this point, the broken branches are in five corresponding loops numbered 11, 16, 7, 7 and 10, where each number represents the number of nodes in each sub-loop. Therefore, [11, 16, 7, 7, 10] can be used to indicate the configuration code of the network structure, thereby significantly reducing the variable dimensions and improving the search efficiency.

B. Simplification of the Reconfiguration Network

According to the basic principle of opening a contact switch and closing a section switch in a loop each time, different basic states are formed because of the different combinations of contact switches, and each basic state can further generate different solutions according to the different section switches. As shown in the simple network in Fig. 2, assume a contact line that is numbered with 10 exists between node 7 and node 10. An approach to find loops is presented in Fig. 3: once the former state of network reconstruction is given, two temporary empty solutions can be established first (all were 0, the length of which is the sum of all the lengths of the branches containing the contact branches); Next, search the parent nodes constantly from two endpoints of the contact switch to identify the corresponding branches. After determining all the branches of the loop, different groups of initial solutions can be obtained by setting the contact switch bit to 1 and one of the bits in the loop to zero.

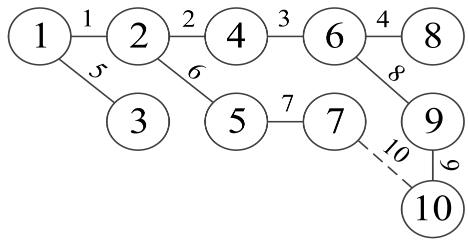

Fig. 2. A simple network with 10 nodes

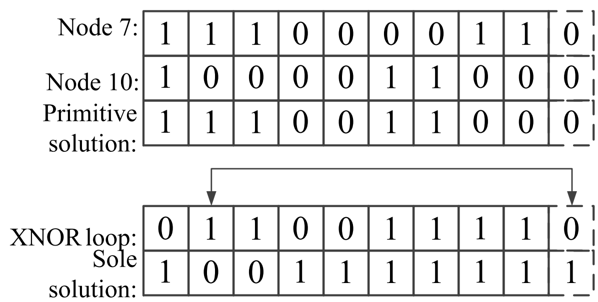

Fig. 3. Approaches of creating original solutions

Following the principle of arbitrarily switching contact switches and section switches, the initial solution space of the network shown in Fig. 3 is 2^{10}=1024. Thus, all the solutions must be traversed to eliminate those that do not meet the conditions. As a result, four solutions can be generated directly.

C. Power Flow Calculation of Distribution Network

Flow calculation models are diverse because of the diversity of DG accessing forms[12]. For example, an asynchronous generator that can be simplified as PQ nodes should be treated as loads that have opposite direction and equal power when power flow is calculated. This model can be represented as:

$$\begin{cases} P = -P_s \\ Q = -Q_s \end{cases} \quad (2)$$

where P_s and Q_s are the active power and the reactive power of the node, respectively.

Photovoltaic cells, which can be connected to the power supply of the power grid through the current inverter, can be treated as *PI* nodes that have constant current and constant injection power. The corresponding reactive power can be calculated by the active power, voltage and current obtained by the iteration method in turn. Next, they can be converted into *PQ* nodes using the formula below.

$$Q = \sqrt{|I|^2 |U|^2 - P^2} \quad (3)$$

The DGs using synchronous generators as interfaces are divided into two types: power factor control and voltage control. The voltage controlled DGs and power factor controlled DGs can be treated as *PV* nodes and *PQ* nodes, respectively.

For power flow calculation of the radial distribution network with only one balancing node (power node) and some *PQ* nodes (load nodes), the back forward sweep algorithm is programmed simply and computed efficiently. The method that has taken the impact of DGs on distribution network into consideration is demonstrated in Fig. 4.

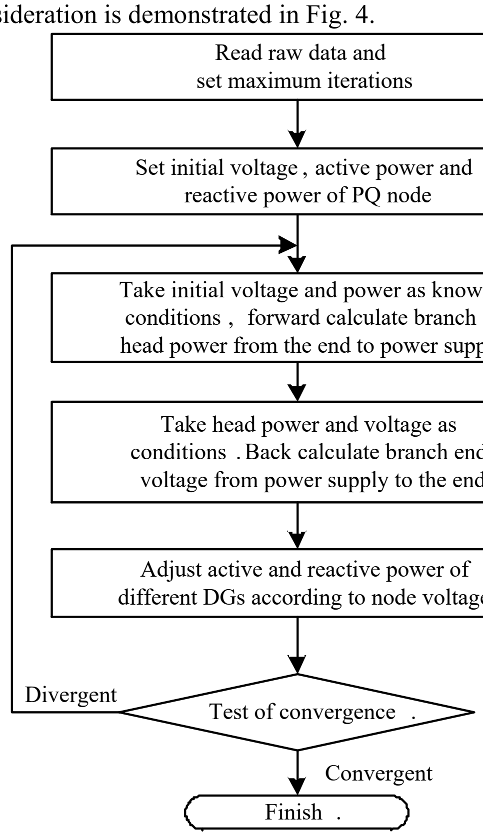

Fig. 4. Power flow calculation with the back forward sweep in the distributed generator

D. Optimization Algorithm Based on the Improved Shuffled Frog Leaping Algorithm

According to the update strategy of shuffled frog leaping algorithm (SFLA), the worst individual that actually evolves toward a better direction under the attraction of the local optimal individual or global optimal individual is not influenced by any other individual.

Based on the ideas presented above, the molecular dynamics algorithm is introduced to the SFLA as a refresh strategy. After referencing the cloud model theory, which is characterized by prone-stability and randomness, and substituting the basic cloud generator for the random update operation in SFLA, the molecular dynamics simulations and cloud model theory-based shuffled frog leaping algorithm (MD-CM-SFLA) is proposed here, the specific steps of which are as follows:

1) Randomly initialize velocity variables of the frog population and the individual. Set the algorithmic parameters, such as the total number of frogs in a population *N*, the dimension of the frog individual (solution) *d*, the number of frogs in a sub-population *m*, the number of sub-populations *n*, the number of local iterations in a sub-population *g*, the number of global blending iterations *G* and the proportion coefficient λ.

2) Calculate the fitness value of each frog individual.

3) Sort all the N frogs according to their fitness value from high to low, and then divide them into n sub-populations.

4) Repeat the following steps g times for each sub-population:

a) Update the optimal individual position of the current iterative sub-population X_b and the global optimal individual position according to the fitness value X_g. Determine the worst individual position of the current iterative sub-population X_w;

b) Update X_w according to formulas (4)-(7):

$$a(k) = \lambda \cdot e^{|r_g - r(k)|} \cdot (r_g - r(k)) \quad (4)$$

$$r(k+1) = r(k) + v(k) + 0.5 \cdot a(k) \quad (5)$$

$$a(k+1) = \lambda \cdot e^{|r_g - r(k+1)|} \cdot (r_g - r(k+1)) \quad (6)$$

$$v(k+1) = v(k) + 0.5 \cdot (a(k) + a(k+1)) \quad (7)$$

where *r(k), v(k) and a(k)* are the current position, velocity and acceleration of the worst individual X_w, respectively, r_g is the position of the global optimal individual, and *r(k+1), v(k+1) and a(k+1)* are the position, velocity and acceleration of the updated individual $newX_w$, respectively.

c) If the fitness value of the updated individual $newX_w$ is better than that of X_w, then X_w should be replaced by $newX_w$; otherwise, X_w should be updated using the basic cloud generator. The concrete steps are as follows:

- Generate a normal random data E_n' having an expected value of $E_n=\Omega/c_1$ and a standard deviation of $H_e=E_n/c_2$;
- Generate a normal random data *x* having an expected value of X_w and a standard deviation of the absolute value of E_n, and then take *x* as a concrete quantization value of the qualitative concept *A*, called the cloud droplet;
- Calculate $y=exp(-(x-X_w)^2/2(E_n)^2)$ and take *y* as the uncertainty of the qualitative concept *A*;
- The whole content of this qualitative and quantitative transformation is completely reflected by *(x,y)*;

Regarding Ω, c_1 and c_2, Ω, is the search range of variables, c_1 is the size of population, and c_2=10.

5) After the local depth search has been completed by all the sub-populations, the global optimal value is output, and the evolution is ended if the number of the global blending iterations is satisfied; otherwise, remix all the frog individuals and go to step four.

E. Improved Algorithm Flow of the Distribution Network Reconfiguration

Based on the description above, the process of the distribution network reconstruction in this thesis is as follows:

1) Input the initial data of the distribution system, including the power supply reference voltage, the numeration of nodes and branches, the load value of each node, and the numeration of loops in which the switches belong; set the corresponding algorithmic parameters.

2) Ascertain the number of loops and the numeration of the corresponding switches according to the coding method in section A, and then generate the initial population of suitable scale randomly.

3) Judge the validity of the initial solutions. Two criteria are chosen in this paper.

a) The number of branches is the total nodes minus 1;

b) No electric "isolated island" exists in the distribution network, i.e., after the corresponding number of switches have been disconnected based on the criterion in Eq. 1, all the load nodes should be connected to power nodes.

4) Determine the efficient solutions by distribution network reconstruction and simplification according to section B. Next, obtain the fitness value of the objective function (network loss) according to the power flow calculation for the efficient solutions with the back forward sweep algorithm demonstrated in section C.

5) Update and optimize the initial population according to the improved SFLA described in section D.

6) Judge if the global optimal solution is converged to according to whether or not the number of iterations has reached the pre-set evolution time: if so, then output the outcome; otherwise, regenerate a population and re-evolve.

IV. EXPERIMENT AND SIMULATION

To verify the effectiveness of the method in this thesis, the IEEE33 node distribution network test system shown in Fig. 1 was chosen for simulation. The system contained 33 nodes and 37 branches, the rated voltage was 12.66 kV, and the total network load was 3607 kW + j2300 kvar. The number of populations was set at 200; the size of sub-populations was 20; the number of sub-populations was 10; and the number of local depth search iterations was 10. The number of global blending iterations was 30; the scale factor was 4; and the individual coding length was 5. The algorithms compared where the PSO, the DE, and the improved SFLA. To determine the adaptability of the method proposed, configuration test simulations were performed before and after the DGs were connected to the distribution network. Among all the experiments, 4 DGs were accessed near a heavy load, and the capacity of each DG was less than the load of the access point. Access positions and capacities of the DGs are presented in Table II.

TABLE II. THE ACCESS LOCATIONS AND CAPACITIED OF DGS

Access location	Capacity /kW	Power factor /pu
6	100	0.8
8	50	0.9
21	50	0.85
24	250	0.9

Fig.5 presents the changes of the active power P and the reactive power Q of each node caused by the network reconstruction based on the improved SFLA. As seen, the variation trends of the active power with nodes pre- and post-network reconstruction were basically the same, whereas P increases were overall slightly larger than those of pre-reconstruction. Marked increases of P were found near the 4 access positions after reconfiguration; in particular, at node 8, the P value rose from 0.6750 MW to 1.4955 MW, with an increase of 121.55%, and the total P value rose from 26.0487 MW to 33.2588 MW. Furthermore, the reactive power of each node became more balanced after reconstruction.

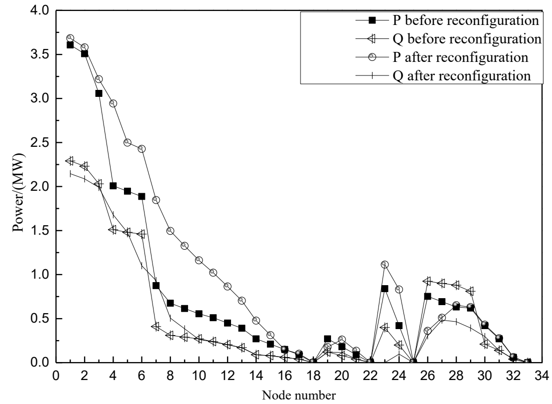

Fig. 5. Comparison of P and Q before and after distribution network reconfiguration

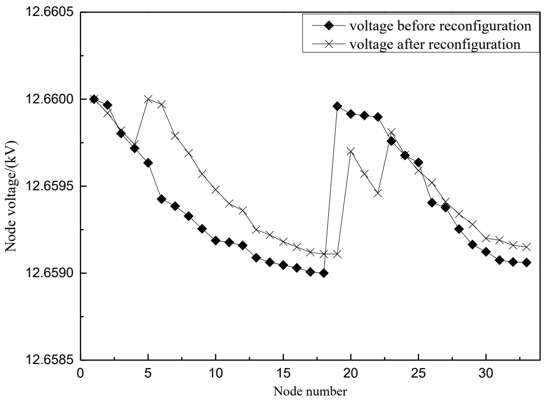

Fig. 6. Comparison of the node voltage values before and after distribution network reconfiguration

The reconstruction simulation based on the improved SFLA of the IEEE33 node distribution network test system was performed, and the voltage changes of each node pre- and post-construction are provided in Fig. 6. What is striking in the figure is the voltage on nodes 6, 8, 21 and 24, where the DG access increased obviously via the reconfiguration. In addition, the system voltage became more stable, and the voltage range reduced from 1 V before the reconstruction to 0.85 V afterwards.

Fig. 7 and Fig. 8 show the active and reactive network loss before and after distribution network configuration. Fig. 7 shows the network loss variation of each node, and the cumulative changes of network loss are presented in Fig. 8.

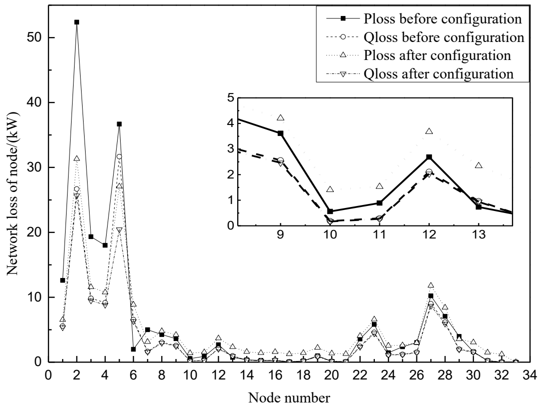

Fig. 7. Comparison of the node network loss before and after distribution network reconfiguration

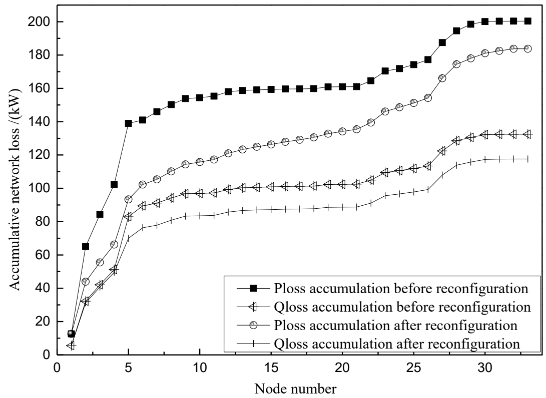

Fig. 8. The cumulative network loss before and after distribution network reconfiguration

Fig. 7 is quite revealing in several ways. First, the active power network loss of the IEEE33 node distribution test system was influenced significantly by the configuration based on the improve SFLA. The configuration to some extent reduced the network loss of high-loss nodes and kept the network loss of low-loss nodes almost constant, thus balancing the system circuit. Regarding the reactive power network loss, the impact of reconfiguration on reactive power network loss of each node Q_{loss} was generally not so large; however, it optimized several nodes with relatively high loss value. According to Fig. 8, configuration simulation of the IEEE33 node distribution network test system did decrease the active and reactive power network loss to varying degrees. The total active power network loss Q_{loss} dropped from 132.449 kW to 117.559 kW, a decrease of 11.24 percent, and the total reactive power network loss P_{loss} declined from 200.331 kW to 183.760 kW, a decrease of 16.57 percent, thereby resulting in a dramatic decrease in economic cost.

In Fig. 9, comparison of the exact solution and the first iteration result of the IEEE33 node distribution network test system shows that the difference of power flow calculation results was smaller if the network load was smaller. In the low network loss interval, the first iteration result was close to the accurate result and can reflect the trend of accurate result completely.

The first iteration error of the active power network loss of the IEEE33 node distribution network test system is calculated in Fig. 10. It can be seen that in the ranges of low P_{loss} (nodes 10-22 and nodes 31-32), the first iteration P_{loss} was lower than the accurate value, whereas it was higher than the accurate value in the ranges of high P_{loss} (nodes 1-9 and nodes 23-31).

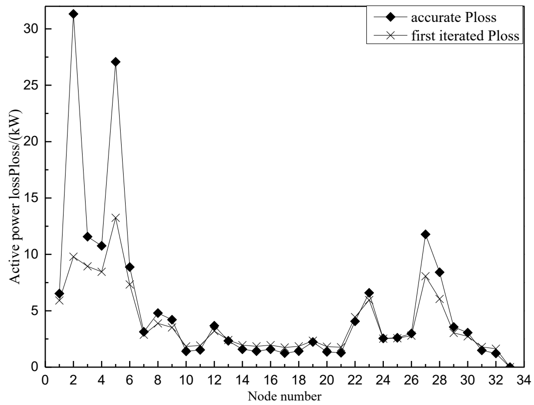

Fig. 9. Result of flow calculation with one iteration

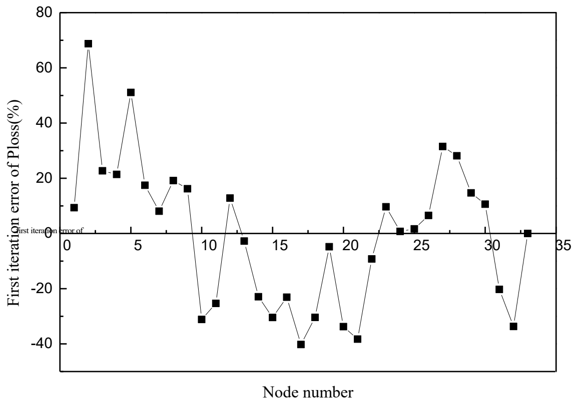

Fig. 10. Error of flow calculation with one iteration

The results of the distribution network reconfiguration simulation test are shown in Fig. 11. It can be seen from the diagram that the network loss of the distribution system after the reconfiguration of DG is greatly reduced, and the quality of the node voltage has been improved effectively. Moreover, DG not only can reduce the network loss further but also provides good support for the node voltage.

In addition, to compare the optimization abilities of the 3 different algorithms considered, the average convergence speeds of 50 simulations under condition of DGs being accessed were summarized, as presented in Table III. It can be inferred that the improved SFLA has prominent optimization ability for the problem of distribution network reconfiguration.

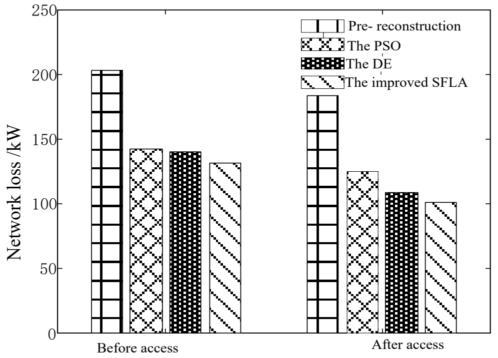

Fig. 11. Performance comparison of distribution network reconfiguration for 3 different algorithms

TABLE III. COMPARISION OF THE CONVERGENCE SPEED

Name of algorithms	**Pre-reconstruction**	**Particle swarm optimization**	**Differential evolution algorithm**	**The improved SFLA**
Average of convergence time (s)		10.5	9.9	5.6
Network loss drop (%)	21.13%	13.99%	21.47%	28.81%

V. CONCLUSION

In this paper, a reconfiguration algorithm of a distribution network based on the improved shuffled frog leaping algorithm was proposed. This algorithm referenced the theory of molecular dynamic simulation, utilized the prone-stability and randomness of the cloud droplet, and adopted a new update strategy for the worst individual, thus effectively balancing the relationship between swarm diversity and search efficiency. Simulations on the IEEE33 test system using this algorithm were conducted, and the conclusions are as follows:

In the IEEE33 node distribution network test system, the P value increased obviously near 4 access positions of the DGs. Moreover, the reactive power Q of each node became more balanced after reconstruction. The voltage on nodes 6, 8, 21 and 24, where DGs were accessed, increased apparently. The system voltage became more stable, and the voltage range reduced from 1 V before the construction to 0.85 V afterwards. After configuration of the distribution network, the power network loss of the IEEE33 node distribution network test system was reduced. The total reactive power network loss Q_{loss} dropped from 132.449 kW to 117.559 kW, a reduction of 11.24 percent, and the total active power network loss P_{loss} declined from 200.331 kW to 183.760 kW, a reduction of 16.57 percent. The algorithm proposed in this paper has high convergence rate, powerful global searching ability and can solve the problems of current algorithms such as slow convergence and ease of descent into a local optimum.

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