Distribution Network Reconfiguration based on Improved Gravitational Search Algorithm

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Abstract. Network reconfiguration for loss reduction in the distribution system is a significant way to save resources. It's an extremely hard optimization problem because of a plenty of switches in a distribution network. This paper presents an efficient Gravitational Search Algorithm (GSA) and its improvement based on elite strategy and adaptive position (ES-APGSA) to reduce grid loss using reconfiguration. The new algorithm can improve the speed of iterations and avoid the local convergence. In addition, the encoding method based on ring network is proposed which makes the dimensions of the particles much lower leading to an acceleration of the process. The correctness and effectiveness of the methods suggested in this paper is verified through the simulation results of IEEE33-node system.

1. Introduction

With the development of society, the requirements of energy economy and quality are increasing gradually. Distribution network as a part which is directly connected to power consumers has a profound impact on the users' feeling and evaluation. How to make the distribution network operation better and securer is becoming a research hot spot today.

Serving as one of the important measures to facilitate optimal operation of distribution, distribution network reconfiguration is lucrative in both economic and social benefit. It is a complex combinatorial optimization process aimed at finding a radial operating structure that minimizes the system power loss, balances the overload of the network, and improves the reliability of power supply [1] while satisfying operating constraints. Because of a large amount of section switches and contact switches in network, the optimization is a multi-objective nonlinear mixed integer problem. The traditional solutions are mathematical optimization theory, optimal power flow and switch exchange method. In recent years, intelligent optimization algorithms have been booming. Genetic algorithm (GA) is applied for reconfiguration in [2], but the coding isn't improved. Ant colony search algorithm (ACSA) improves the speed of iterations with a better performance than GA in [3]. With the development of computers, artificial neural network (ANN) provides a new method to this problem but can't explain the essence of reconfiguration in [4].

This paper mainly focuses on a new method based on improved GSA including elite strategy and adaptive position to solve network reconfiguration of distribution system for power loss reduction, and encoding strategy of GSA is also studied.

2. Distribution network reconfiguration model

2.1. Objective function

The objective function of network reconfiguration is to minimize the total power losses in the condition of operating constraints in the distribution system. With the assumption that the loss due to line reactance is negligible, the objective function can be expressed by equation (1).

$$\min f = \sum_{j=1}^{N} R_j \frac{P_j^2 + Q_j^2}{U_j^2} \tag{1}$$

where f is line losses in the whole system, N is the number of branches, R_j is the resistance in the j-th branch, P_j and Q_j are the power flow, U_j is the voltage at the terminal of j-th branch.

2.2. Constraints

Reconfiguration must meet the constraints or else, the objective function value is set to a penalty value for avoiding this computation.

2.2.1. Power flow constraint.

Power flow must be met in the process of every reconfiguration which makes distribution network topology change.It is sure that the result is correct.The forward-backward sweep method is generally adopted in power flow calculation of distribution network while its radial structure.

2.2.2. Inequality constraints.

The results of line flows and node voltages can't be exceeded as in equation (2).

$$\begin{cases} S_j \le S_{j\max} \\ U_{i\min} \le U_i \le U_{i\max} \end{cases} \tag{2}$$

where S_j and $S_{j\max}$ are power flow and maximum capacity in j-th branch, Ui is i-th node voltage, $U_{i\min}$ and $U_{i\max}$ are minimum voltage and maximum voltage.

2.2.3. Radial structure constraint.

A distribution network is designed in a closed loop and operated in an open loop. The topology after reconfiguration must be radial while there are no islands or acnodes.

2.3. Forward-backward sweep method

The distribution network power flow calculation based on forward-backward sweep method is faster than Newton-Raphson method, and the former requires initialization less. To make the result correct, hierarchical node optimization is needed because of data about head-foot nodes in the branches changing with each reconfiguration.The each node is picked out in layers in accordance with the current flow. The power supply node is the first layer, all the nodes connected with supply node are belong to the second layer, and so on. The nodes are renumbered according to the layered order which is used for the next power flow calculation.

3. Coding and feasibility analysis

A distribution network is designed in closed loop and operated in open loop. Generally, the reconfiguration is encoded in each switch state and it leads to too long codes and complicated calculation. Therefore, ring-based coding is necessary to solve this problem.

3.1. Ring-based coding principles

According to the number of contact switches, the system is divided into equivalent minimum loops which require a ring with the shortest distance and no common branch with each other.In the process of reconfiguration, only the switches in loops are open.

3.2. Radial structure judgment

In order to avoid rings in the system, the switches in noncommon branches must be open. As multi-loops, judging the radial network is the same as judging the open switch in common branch or for two loops. There are two undesirable cases, one is that the open switch is same and the other is that the open switch is in common branch in two loops.

3.3. Connectivity judgment

The judgment of connectivity is mainly generated connectivity matrix which is defined as:

- The rows and columns of the matrix are different nodes.Each element t_{ij} is stated for the branch existence that '1' represents a branch from *i*-th node to *j*-th node and '0' stands for no branch.
- The diagonal of this matrix represents the total number of branches in connection with this node. Its value equals to the sum of '1' in this row and column.

If a diagonal element is '0', the node corresponding to it is solitary. The island is no power flow through it and can be found in the process of hierarchical node optimization.

4. Gravitational search algorithm and improvements

4.1. Gravitational search algorithm

Gravitational search algorithm is a heuristic optimization method based on the law of universal gravitation and Newton's second law, referred to as GSA[5].The GSA seeks the optimal solution by the masses of the objective space moving through the medium of information communication, gravitational force. The optimal solution will be found when the masses move to the optimal position.

The GSA initializes the position and velocity in the solution space and velocity space firstly, where the position represents the solution. The position and velocity of the *i*-th search particle in the D-dimensional space are expressed as in equation (3).

$$\begin{cases} X_i = (x_i^1, \cdots, x_i^d, \cdots, x_i^D) \\ V_i = (v_i^1, \cdots, v_i^d, \cdots, v_i^D) \end{cases} \tag{3}$$

where x_i^d and v_i^d represent position and velocity.

The mass of ith particle is defined as in equation (4) and equation (5).

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{4}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{N} q_j(t)} \tag{5}$$

where $fit_i(t)$ and $M_i(t)$ represent the fitness value and the mass of *i*-th particle at the *t*-th iteration; $best(t)$ and $worst(t)$ represent the best and worst fitness value of all the particles at the *t*-th iteration.

The algorithm originates from the simulation of the law of universal gravitation but does not rigidly adhere to the exact formula of universal gravitation. According to the experimental results, on the *d*-dimension, the gravitational force of *i*-th particle is defined as equation (6).

$$F_{ij}^d(t) = G(t)\frac{M_i(t)M_j(t)}{R_{ij}(t) + \varepsilon}(x_j^d(t) - x_i^d(t)) \tag{6}$$

where $R_{ij}(t)$ is the Euclidean distance from *i*-th to *j*-th particle. ε is a constant for denominator not zero. $G(t)$ represents the value of the gravitational constant at the *t*-th iteration as equation (7).

$$G(t) = G_0 e^{-\alpha t/T} \tag{7}$$

where G_0 and α are constants, T is the maximum number of iterations.

The resultant force of *i*-th particle on the *d*- dimension is represented as equation (8).

$$F_i^d(t) = \sum_{j \neq i}^{N} F_{ij}^d(t) \tag{8}$$

According to the Newton's Second Law, the acceleration of *i*-th particle on *d*-dimension is defined as equation (9).

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{9}$$

Then velocity and position are updated as in equation (10).

$$\begin{cases} v_i^d(t+1) = r \times v_i^d(t) + a_i^d(t) \\ x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \end{cases} \tag{10}$$

The basic GSA is sufficient to optimize some problems but there are many challenges such as a waste of time and difficulty of convergence. Therefore, the GSA is supposed to be improved.

4.2. Improvements of GSA

Elite strategy and adaptive position are both applied for GSA. Improved GSA is called ES-APGSA.

4.2.1. Elite strategy.

When calculating the resultant force, some particles with pretty low mass can be neglected due to slight influence on others. It is called "Elite Strategy". It is wise to take the particles with high mass into consideration which have strong gravitational force. A larger particle occupies a better position, representing a better solution. Doing so can eliminate the influence on a large mass caused by a short distance. So all the particles move closer to the one with the largest mass gradually and ultimately reach the position representing the optimal solution. Therefore, it's necessary to make changes to resultant force in equation (8) as equation (11).

$$F_i^d(t) = \sum_{j \in kbest, j \neq i}^{N} rand_j \cdot F_{ij}^d(t) \tag{11}$$

where $rand_j$ represents a random variable which is uniformly distributed between [0,1]. *kbest* indicates particles' mass is in descending order of the first *k* individuals and the *k*-value decreases linearly from *N* to 1 with the iterations changing.

4.2.2. Adaptive position.

There are essential differences between the particle swarm optimization algorithm (PSO) and GSA, but their models are both based on updates of the velocity and position.

Inspired by improvement of PSO[6], the paper introduces a new coefficient *s* in the position updating equation of GSA as equation (10). This coefficient is a kind of constriction factors and makes rangeability of position accommodate iterations. Constriction factor 's' is better to take the form of the variable and its expression is equation (12).

$$s = s_{\max} - (s_{\max} - s_{\min})\frac{t}{T} \tag{12}$$

where *t* represents the iterations at present, *T* represents the maximum number of iterations. s_{max} and s_{min} represent the upper and lower bounds of *s* which are 1 and 0.

Taking *s* into consideration, the position updating changes into equation (13) .

$$x_i^d(t+1) = s \cdot x_i^d(t) + v_i^d(t+1) \tag{13}$$

5. Steps of reconfiguration

1) Read the raw data including the node powers, the branch data, the reference voltages and powers.
2) Calculate the voltage of each node and the total loss.
3) Do ES-APGSA.
   a. Initialize velocity and position.
   b. Calculate the fitness values of all the particles. The best is global optimal value expressed as F_{best} and the position of the particle is global optimal solution expressed as X_{gbest} while the position is X_{pbest} in every iteration。
   c. Update mass and gravitational constant.
   d. Calculate the resultant force with ES.
   e. Calculate the acceleration and update velocity and position with constriction factor. Note that the positions should be rounded.
   f. Repeat steps b~e until maximum iteration.
4) Optimal computation more than once and analyze results.
5) Choose the best in step(4) as final result and compare it to result in step(2).

6. Case study

A typical distribution system IEEE33-node, as shown in figure 1, which was studied in [1] is taken as a case study to test the performance of the ES-APGSA.

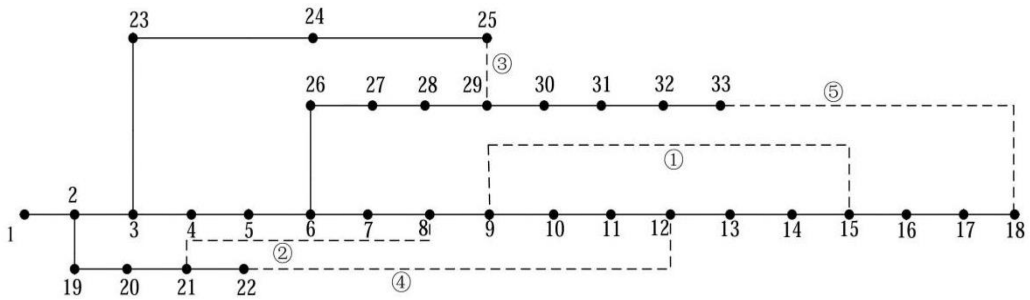

Figure 1. IEEE33-node distribution system

In this system, the total load power is 3715kW+j2300kvar, the base voltage is 12.66kV and the base capacity is 10MVA. There are 32 section switches and 5 contact switches. 1st node is the power supply. Before reconfiguration, the line loss is 202.67kW and the lowest voltage is 0.9131p.u. for 18th node in the context of the contact switches open. According to coding principle, the dimension of each particle in GSA is 5 and the number of particles in a group is set to 10. It iterates 100 times every GSA and the reconfiguration is repeated 30 times.

There are convergence curves using GSA and ES-APGSA for 30 times as figure 2 and figure 3.

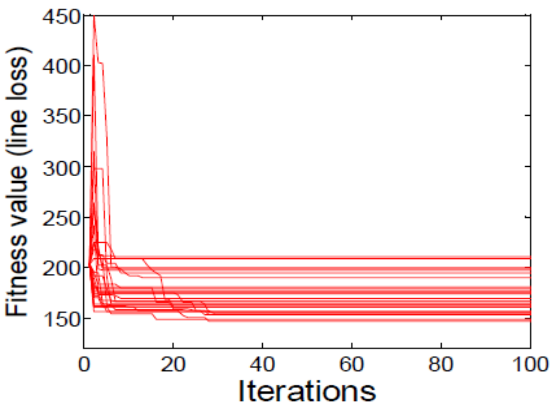

Figure 2. The convergence curves in GSA

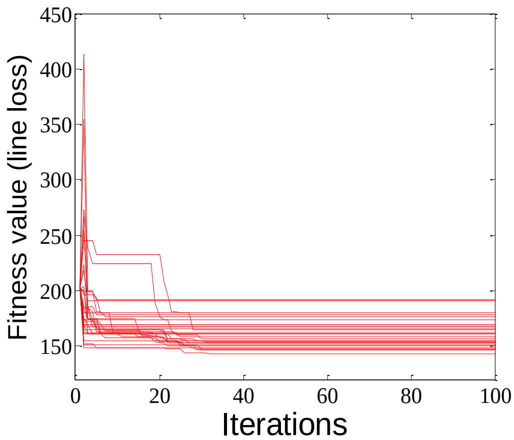

Figure 3. The convergence curves in ES-APGSA

Figure 2 shows that in GSA, some convergence results is unsatisfactory because they are worse than before, and a few results can reach around best. ES-APGSA has a better performance that all the results are better in some degree and most of them are near the best. The detailed results are shown in table 1 and compared to PSO-w studied in [6].

After reconfiguration using ES-APGSA, the total line loss decreases from 202.6762kW to 139.9767kW by 30.94% and the voltage levels are improved in this system. The performance of ES-APGSA is much better than others.

Table 1. Statistical results of the different methods.

	Before Optimization	PSO-w	GSA	ES-APGSA
Minimum value	202.6762	143.2957	144.0234	139.9767
Mean value	--	165.3088	167.8482	158.3088
Variance	--	385.8687	324.2321	104.0764
Optimal open branch	9-15, 8-21, 25-29, 12-22, 18-33	14-15, 7-8, 27-28, 9-10, 32-33	14-15, 7-8, 27-28, 10-11, 32-33	14-15, 7-8, 28-29, 9-10, 32-33
Lowest voltage	0.9131(18th node)	0.9401(32nd node)	0.9398(32nd node)	0.9413(32nd node)

7. Conclusions

An improved GSA has been proposed for distribution loss minimum reconfiguration. The gravitational force is a way of transferring information between different particles and leads the particles to the optimal position representing the solution. ES-APGSA is improved in elite strategy and adaptive position to accelerate the calculations. Also, the encoding method based on ring network is successfully used for dimensionality reduction. The effectiveness of the ring-based encoding and ES-APGSA has been investigated on IEEE33-node system showing promising results when compared with PSO-w and others. This gives an advice to the decision makers to optimize system operation.

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