A distribution network reconstruction method with DG and EV based on improved gravitation algorithm

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Abstract
In order to solve the problem of distribution network reconstruction with distributed generation (DG) and electric vehicle (EV), a multi-objective distribution network reconstruction model with DG and EV is established in this study. Two rules for opening the loop are proposed to reduce the probability of infeasible solutions. Some measures are proposed to improve traditional gravitational algorithm (GSA). Firstly, the particle swarm algorithm (PSO) is combined to improve the update formula of speed and position. In this way, the global search capability of the GSA is enhanced, which gives the best performance with respect to jump out of the local traps. Furthermore, the processing method for agents that cross the boundary is improved, which increases the diversity of samples while generating elite particles. Hence, this method can improve the efficiency of the algorithm. Finally, the variability of load, DG and EV is considered for dynamic reconstruction. The validity of the optimization algorithm and refactoring strategy are demonstrated by case studies in the paper.

1. Introduction
In recent years, with the consumption of traditional fossil energy and the demand for environmental protection, a large number of DG and EV have been connected to the distribution network. The popularization of DG and EV has obvious advantages in energy saving and environmental protection. However, due to the randomness of the DG and EV loads, it may change the system power flow and expand the difference between the load peak and valley, which will have a huge impact on the power quality and power system stability (Li et al., 2017; Mirjalili & Lewis, 2014; Qian et al., 2011). The current research focus of distribution network reconstruction is how to use the advantages of DG and EV grid connection to ensure the stability of the distribution network.

Distribution network reconfiguration (DNRC) is realized by changing the status of sectionalizing switches and is usually done for loss reduction (Wang et al., 2018). Significant research work has been done on DNRC, and there are three main types of algorithms including traditional mathematical optimization algorithms (Marti et al., 2013), heuristic algorithms (Bose et al., 2012), and artificial intelligence algorithms. In Zhang and Yuan (2014), a new genetic algorithm for distribution network reconstruction based on all spanning trees of undirected graphs is proposed, which reduces infeasible solutions, but the algorithm is easy to fall into local traps and is not suitable for the scene with large scale and high complexity. In Xu et al. (2018), three coding rules were proposed and improved Firefly algorithm was adopted for reconstruction, which improved the calculation efficiency, but the shortcoming was that only the static reconstruction problem was considered. In Zhang et al. (2018), EV and DG are added to the reconstruction problem. A multi-objective reconstruction model is established, but the reactive power optimization of the distribution network is not considered in the study. In Liang et al. (2017), in order to solve the problem of large scale and complex calculation, the advantage of PSO’s strong global search ability is used to improve the Harmony Search Algorithm (HS) to make the algorithm can find the global optimal solution easier, but the programme is so complicated that the calculation speed is slow.

To handle the problems identified above, the main contributions of this paper can be summarized from the following aspects. (1) Three coding rules are adopted to simplify the network topology. Two delooping rules are proposed to reduce the probability of infeasible solutions and improve the speed of calculation. (2) In order to make it easier for the algorithm to jump out of the local trap, the memory function of PSO is combined to generate dynamic learning factor to improve the speed and
position update formula of GSA. The transboundary processing method of GSA has been improved to pull the transboundary particles back to the vicinity of excellent particles, which not only preserves the sample diversity, but also increases the number of elite particles so that the convergence speed of the algorithm is improved. (3) The variability of load, DG output and EV charging load is considered to establish an equivalent daily load curve. This strategy results in lesser the number of switching operations in dynamic reconstruction.

The remainder of the current paper can be outlined as follows. In Section 2, A multi-objective mathematical model for distribution network reconfiguration was established. In Section 3, Three topological structure simplification rules are adopted and two open-loop rules are proposed to improve the distribution network reconfiguration strategy. In Section 4, Two improvement measures were proposed to make GSA perform better in the optimization process. In Section 5, The advantages of algorithms and refactoring strategies in this paper are verified by simulation and experiment. Finally, the paper is concluded in Section 6 and some future works are also provided.

2. Mathematical model of distribution network reconfiguration

2.1. The objective function

The distribution reconfiguration belongs to a complex combinatorial optimization problem. The various network performances in terms of multi-objective function include minimization of system power loss, voltage deviation and load deviation:

(1) The minimal network loss:

\[ f_1 = \min \sum_{i=1}^{n} k_i R_i \frac{P_i^2 + Q_i^2}{U_i^2}, \]  

where \( n \) is the total number of branches; \( k_i \) is the switching state of branch \( i \), 0 is open, 1 is closed; \( R_i \) is the total resistance of branch \( i \); \( P_i, Q_i, \) and \( U_i \) are the terminal active power, reactive power and node voltage at the end of branch \( i \), respectively.

(2) The minimal voltage deviation:

\[ f_2 = \min \sum_{j=1}^{N} \left( \frac{U_j - U_{js}}{U_{js}} \right)^2, \]

where \( N \) is the total number of nodes; \( U_j \) is the actual voltage of node \( j \); \( U_{js} \) is the rated voltage of node \( j \).

(3) The minimal load deviation:

\[ f_3 = \min \sum_{i=1}^{m} \left( \frac{S_i}{S_{i \text{max}}} \right)^2, \]

where \( m \) is the total number of closed branch; \( S_i \) and \( S_{i \text{max}} \) indicate, respectively, actual and maximum value of complex power on branch \( i \).

(4) Normalization of the objective function:

The random weight distribution method is adopted to normalize the objective function:

\[ \omega_i = \frac{\text{rand}_i}{\sum_{i=1}^{n} \text{rand}_i}, \]

\[ f = \min \left( \omega_1 F_1 + \omega_2 F_2 + \omega_3 F_3 \right), \]

where \( \omega_i \) is the random weight coefficient of the objective function \( i \), rand is a random numbers in the range [0,1], \( F_i \) is the minimum value of each iteration of the objective function \( i \).

2.2. The restrictions

(1) Constraints on power balance:

\[ \begin{align*}
    P_G - P_i - U_i \sum_{j=1}^{n} U_i (G_{i,j} \cos \theta_{i,j} + B_{i,j} \sin \theta_{i,j}) &= 0 \\
    Q_G - Q_i - U_i \sum_{j=1}^{n} U_i (G_{i,j} \cos \theta_{i,j} + B_{i,j} \sin \theta_{i,j}) &= 0
\end{align*} \]

(6)

where \( P_G \) and \( Q_G \) indicate, respectively, active power and reactive power of DG injected node, \( P_i \) and \( Q_i \) indicate, respectively, active power and reactive power of node load.

(2) Constraints for system operation:

\[ \begin{align*}
    U_{\text{min}} &\leq U_i \leq U_{\text{max}} \\
    I_{\text{min}} &\leq I_i \leq I_{\text{max}} \\
    S_i &\leq S_{\text{max}} \\
    P_G &\leq P_{G_{\text{max}}}
\end{align*} \]

(7)

where \( U_{\text{min}} \) and \( U_{\text{max}} \) indicate, respectively, the upper and lower voltage limits of node \( i \), \( I_{\text{min}} \) and \( I_{\text{max}} \) indicate, respectively, the upper and lower current limits of branch \( i \), \( S_i \) is the complex power of branch \( i \), \( P_{G_{\text{max}}} \) is the maximum output of DG.

2.3. Mathematical model of DG

(1) Model of photovoltaic power output
The output power of solar power can be calculated as follows:

\[ P_{PV} = \eta P_{rate} \frac{A}{A_s} [1 + \alpha_p (T - T_{STC})] \]  

(8)

where \( \eta \) is the power factor, \( P_{rate} \) is the rated power, \( A \) is the actual light intensity, \( A_s \) is the light intensity under standard test conditions, \( \alpha_p \) is the power temperature coefficient, \( T \) is the current surface temperature of the photovoltaic cell, and \( T_{STC} \) is the temperature of the photovoltaic cell under standard test conditions.

(2) Model of wind power output

The output power of wind power depends mainly on the wind speed, which can be expressed as follows:

\[ P_t(v) = \begin{cases} 
0, & 0 \leq v \leq v_{ci} \\
0.5v^3 - bP_r, & v_{ci} \leq v \leq v_r \\
P_r, & v_r \leq v \leq v_{co} \\
0, & v_{co} \leq v 
\end{cases} \]  

(9)

where \( P_t \) is the rated power, \( v_{ci}, v_r \) and \( v_{co} \) indicate, respectively, the minimum wind speed that can be output, the rated wind speed and the highest wind speed that can be output, \( v \) is the actual wind speed.

The DG output can be regarded as a set of continuous real variables, and the simplest treatment for it is to treat it as a ‘negative’ load. DG can be viewed as a PQ node if its active power and power factor are determined:

\[ \begin{align*} 
P &= -P_s \\
Q &= -Q_s 
\end{align*} \]  

(10)

where \( P_s \) and \( Q_s \) indicate, respectively, active power and reactive power of DG.

3. Distribution network reconstruction strategy

In this study, the opening and closing of the branch is represented by the numbers 0 and 1, 0 is open and 1 is closed. However, this encoding method will cause the explosion of the dimension of the solution vector, and a large number of infeasible solutions will be generated. In order to avoid this problem, in Xu et al. (2018), three rules for encoding are adopted to simplify the topology:

(1) In the operation of simplification, only the nodes with a dimension of 3 remain.

(2) Since the independent branches that do not constitute a loop will inevitably form an island when its switches are opened, it may not consider the disconnection of its branch switches.

(3) According to the power flow equations, the switches which are connected directly to a power source generally are not considered.

![Figure 1. The simplified topology of 33-bus distribution system.](image1)

![Figure 2. Branch numbers in the simplified network.](image2)

Figure 1 is the simplification of the topology by the rules. The branches of the simplified network are renumbered in Figure 2.

The branch group incidence matrix \( G \) is generated according to Figure 2.

\[ G = \begin{bmatrix} 
1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
1 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 
\end{bmatrix} \]

where, the basic loop is represented by rows, the branch group relation is represented by columns, the loop containing the branch group is represented by 1, and the loop not containing the branch group is represented by 0.

In order to solve the problem that a large number of infeasible solutions will appear in the process of opening the loop, two rules of opening the loop are proposed as follows:

(1) The particle dimension is determined by the number of basic loops, and is sorted according to the order of the number of branch groups from small to large, which can avoid the situation that no branch group can be open at last.

(2) First, a closed branch group in the first row of the matrix \( G \) is selected and set to zero, then all the values of its column are set to zero. This operation
is performed on each row of G. Finally, after the branch group that needs to be opened is selected, the branch contained in these branch group is randomly opened.

In this way, each branch group can be selected at most once. The probability of an infeasible solution is reduced. The calculation time of the algorithm is reduced, and the calculation efficiency is improved.

4. Improvement of gravitation algorithm

4.1. Gravitational search algorithm

Gravitation algorithm (Rashedi et al., 2009) is a new heuristic optimization algorithm based on the law of gravitation and Newton’s second law in physics. Agents with higher quality occupy a better position in the entire search space. Due to the effect of gravity, the greater attraction comes from the larger agents, which attracts smaller agents to approach the optimal position.

The location of agent $i$ can be expressed as

$$X_i = (x_i^1, x_i^2, x_i^3, \ldots, x_i^n); \quad i = 1, 2, 3, \ldots, N$$ (11)

where $x_i^k$ is the position of agent $i$ in dimension $k$.

The quality of the agent can be calculated as

$$m_i(t) = \frac{fit_i(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)}$$ (12)

where $fit_i(t)$ is the fitness of agent $X_i$, best$(t)$ and worst$(t)$ indicate, respectively, The best and worst fitness at time $t$, $M_i(t)$ is the quality of agent $i$ at time $t$.

At a certain moment, the gravitational force of agent $j$ on particle $i$ can be expressed as

$$F_{ij}^k(t) = G(t) \frac{M_{ij}(t) \times M_{ip}(t)}{R_{ij}(t) + \varepsilon} \times (x_j^k(t) - x_i^k(t))$$ (13)

$$G(t) = G_0 \times e^{-\alpha t/T}$$ (14)

where $\varepsilon$ is a small fixed value, $G(t)$ is the gravitational constant at time $t$, $G_0$ is the value of $G(t)$ at the first iteration, $T$ is the maximum number of iterations.

The total gravity of the agent $i$ in dimension $k$ can be expressed as

$$F_i^k(t) = \sum_{j=1,j \neq i}^{N} \text{rand} F_{ij}^k(t)$$ (15)

The update formula of the speed and position of agent $i$ is follow as

$$\begin{cases}
\psi_i^k(t + 1) = \text{rand} \times \psi_i^k(t) + \alpha_i^k(t) \\
x_i^k(t + 1) = x_i^k(t) + \psi_i^k(t + 1)
\end{cases}$$ (17)

4.2. Measures for improving gravitation algorithm

In order to improve the traditional gravitation algorithm to improve its performance and apply it to practical problems, many scholars have conducted research (Kumar et al., 2017; Rashedi et al., 2010). In Li and Zhou (2011), the optimized performance of GSA has been proved to be superior to PSO and genetic algorithm (GA). Two measures are proposed to improve GSA in this paper.

(1) Improvement of speed update formula

In the process of GSA optimization, only the environment of the individual is concerned, and the memory of the overall experience is lacking. By adding individual optimal value $p_{best}$ and group optimal value $g_{best}$ in PSO to the optimization search, the global information exchange capability is enhanced. The speed update formula of GSA is changed as

$$\begin{cases}
\psi_i^k(t + 1) = \text{rand} v_i^k(t) + M_1 + M_2 + \alpha_i^k(t) \\
M_1 = c_1 \times \text{rand} \times (p_{best} - x_i^k(t)) \\
M_2 = c_2 \times \text{rand} \times (g_{best} - x_i^k(t))
\end{cases}$$ (18)

where $c_1$ and $c_2$ are learning factors for PSO, $\text{rand} 1$ and $\text{rand} 2$ are random numbers in the range [0,1]. In order to balance the global search ability and local mining ability of the algorithm, the dynamic learning factor is adopted:

$$\begin{cases}
c_1 = 1 - e^{-\beta(t/T)} \\
c_2 = e^{-\beta(t/T)}
\end{cases}$$ (19)

where $t$ is the current iteration number, $T$ is the maximum number of iterations, $\beta$ is a constant.

(2) Improvement of beyond range processing rules

The common treatment method for transboundary agents is to abandon or pull back to the border. The first method will reduce the sample diversity, and the second method will cause a large number of particles to gather at the boundary, which are not conducive to algorithm convergence. In this paper, the elite strategy is combined to bring the transboundary agent back to a position near the best agent. In this way, the diversity of samples is preserved, and the newly generated agents have better fitness values. In addition, it would be worthwhile to note that this strategy also results in increasing the number of elite agents so that GSA can converge more quickly.
If $x_i \geq x_{\text{max}}$ or $x_i \leq x_{\text{min}}$, a new agent $x_{\text{new}}$ is generated:

$$x_{\text{new}} = x_{\text{best}} + R$$  \hspace{1cm} (20)

$$R = L \times \text{rand}(-1.5, 1.5)/D$$  \hspace{1cm} (21)

where $L$ is the Euclidean distance between the best agent and the agent closest to it in the current iteration. $D$ is the dimension of the agent.

5. Simulation analysis

5.1. Basic data of the system

In this section, the 33-bus distribution system is selected as an example. The initial parameters are set as follows. (1) Initial parameters of the network: the total load of the distribution system is $3715 + j2300$ kV·A, which includes 33 nodes, 37 branches, and 5 tie switches, other detailed network parameters are available from Goswami and Basu (1992). (2) The initial parameters of the algorithm: the population is 60, and the maximum number of iterations is 80, $G_0$ is 50, $\alpha$ is 25, $\beta$ is 2. (3) The access location and capacity of DG are shown in Table 1. (4) At nodes 23 and 10, EV charging stations are installed. Each charging station contains 25 EVs. The capacity of each EV battery is 33.8 kW·h. The structure of the distribution network is shown in Figure 4.

| Number | Kinds | Location | Capacity |
|-------|-------|----------|----------|
| DG1   | WT    | 15       | 600 kW   |
| DG2   | PV    | 30       | 400 kW   |

5.2. Static reconstruction analysis

For demonstrating the impact of reconfiguration, the static reconfiguration of the distribution network is based on the system situation at a certain moment. The DG output is assumed to be a constant value, which is 70% of the rated output. Four scenarios were established for reconstruction analysis. The results are shown in Table 2 and Figure 5:
In Table 2, it can be seen that the network loss before reconstruction without DG is 202.68 kW, and the network loss drops to 139.52 kW after reconstruction. The decrease is about 31.17%. It is also seen that both load balancing and voltage deviation are significantly reduced, which strengthens the stability of the distribution network operation and shows the effectiveness of the reconfiguration method in this paper. The network losses before and after reconstruction with DG are 111.80 and 84.36 kW, respectively. With reference to Figure 5, DG is effective in reducing network loss, balancing load, increasing voltage amplitude and reducing voltage deviation (Table 3).

Further evaluating the effectiveness of the proposed scheme, Under the 33-bus network without DG, the obtained results also compared and indicated that better network reconstruction achieved with both network loss and lowest node voltage over Paper 17 (Chen et al., 2015) and Paper 18 (Liu et al., 2019).

In this paper, the situation of opened switches is the same as in the paper 17, and the forward power generation method is used to calculate the network power flow. The network loss decreased by 31.17% compared with the network loss before the reconstruction. Test results indicated that the effectiveness of the algorithm in this paper is verified.

It can be observed from Figure 6 and Table 4 that the three intelligent algorithms are similar in iterative accuracy. However, the algorithm in this paper has a better precision. In terms of optimization efficiency, after the above three algorithms are run 20 times respectively, the computational results for the test systems confirm that improved GSA is more likely to obtain the global optimal solution in less time than the others.

### Table 2. Comparison of reconstruction results.

| Number | Scenes                          | Opened switches  | Network loss/kW | Load balancing | Voltage deviation/p.u. |
|--------|--------------------------------|------------------|----------------|----------------|------------------------|
| 1      | Before reconstruction without DG | 8–21, 9–1512–22, 18–33, 25–29 | 202.68         | 1.084          | 0.117                  |
| 2      | Before reconstruction with DG   | 8–21, 9–1512–22, 18–33, 25–29 | 111.80         | 0.724          | 0.053                  |
| 3      | After reconstruction without DG  | 7–8, 14–159–10, 32–33, 25–29 | 139.51         | 0.685          | 0.047                  |
| 4      | After reconstruction with DG     | 7–8, 14–159–10, 31–32, 25–29 | 84.36          | 0.481          | 0.029                  |

### 5.3. Dynamic reconstruction analysis

In fact, DG output and EV charging load are not fixed. Their variability is considered for dynamic reconstruction in this paper.
Table 4. Comparison of reconstruction results.

| Algorithm                      | Network loss/kW | Average number of iterations | Average time/s |
|--------------------------------|-----------------|------------------------------|---------------|
| Improved CS                    | 139.993         | 24                           | 23.2          |
| Improved HS                    | 140.246         | 14                           | 18.5          |
| Algorithm in this paper        | 139.513         | 8                            | 13.6          |

Figure 7. Orderly charging load changes of EV.

Figure 8. The forecast of DG output.

The Monte Carlo method (Luo, 2019) is used to simulate the orderly charging of the electric vehicle during the day. The discrete values of each period are shown in Figure 7:

After connecting DG as shown in Table 1, based on a day ahead forecasted data, their predicted output is shown in Figure 8.

Considering the load type, proportion and output of each node (Yang et al., 2009), the change of daily load is shown in Figure 9.

The equivalent daily load curve is established, and the information entropy period division method is adopted to segment the load curve as shown in Figure 10.

The load segmentation shown in Figure 10 is adopted for dynamic reconstruction, and the results are as follows.

From Tables 5 and 6, we can see that the network loss obtained by the two dynamic reconstruction methods is not much different. However, the load segmentation reconstruction method greatly reduces the number of switching operations and saves the cost of switching operations, which also extends the available time of switching. Certainly, this method has positive impacts in DNRC.

Table 5. Load segmentation reconstruction results.

| Period      | Opened switches | Network loss/kW |
|-------------|-----------------|-----------------|
| 1:00–7:00   | 7–8, 12–13, 8–931–32, 25–29 | 25.855          |
| 8:00–13:00  | 7–8, 13–14, 9–1032–33, 25–29 | 380.675         |
| 14:00–18:00 | 7–8, 13–14, 9–1032–33, 25–29 | 518.661         |
| 19:00–20:00 | 7–8, 9–15, 10–1132–33, 25–29 | 330.522         |
| 21:00–24:00 | 7–8, 9–15, 9–1031–32, 25–29 | 71.121          |

Table 6. Comparison of reconstruction results.

| Dynamic reconstruction method | Number of switch actions | Network loss/kW |
|-------------------------------|--------------------------|-----------------|
| No segment                    | 45                       | 1288.230        |
| Segment                       | 7                        | 1326.713        |
6. Conclusion
In this paper, the economics and reliability of distribution network operation are considered, and system loss, load balance, and voltage deviation are used as targets to establish a reconstruction model. Two rules for opening loops were proposed to reduce the probability of occurrence of infeasible solutions and shorten the calculation time. POS is combined to improve the global search capability of GSA. The processing method of the agent beyond the boundary is modified to improve the search efficiency of GSA. The variability of node load, DG output and EV electric vehicle load is considered to establish equivalent daily load and segment it for dynamic reconstruction. By adopting this dynamic reconstruction method, for the switch, the number of actions is reduced, the available time is extended, and the operating cost is saved. The effectiveness of the method of this paper is proved by engineering examples.

In future work, we will focus on (1) comprehensive optimization of distribution network combined with reconstruction and reactive power optimization and (2) the impact of high permeability DG on the operation of distribution network.

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