Dynamic reconfiguration of unbalanced distribution network considering DG uncertainties

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Abstract. In order to solve the multi-objective dynamic reconfiguration problem of the unbalanced source distribution network, this paper proposes a multi-objective dynamic reconfiguration strategy for active distribution network based on affine number. The affine number is introduced in this paper to describe the uncertainty of distributed generation output. The active network loss, voltage deviation and load balance are the objective functions, the dynamic reconfiguration of unbalanced distribution network is modeled. The multi-objective particle swarm optimization algorithm based on Pareto entropy and parallel mesh is used to obtain the static reconfiguration solution in hours. Finally, a reconfiguration time division scheme based on Mahalanobis distance and target expectation is proposed, and the time period is divided again until the switch action constraint is satisfied.

1. Introduction
At present, the proportion of distributed generator (DG) connected to the distribution network (DN) is gradually increasing. For the DN, DG output has a large uncertainty, which poses a greater challenge to select the operation mode of the DN. Therefore, it is of great significance to study the distribution networks reconfiguration (DNR) with uncertain factors.

In practice, the DG output changes with time. Static DNR can only deal with reconfiguration under single time section, which is often used for DN planning. Therefore, the dynamic DNR has more practical value and research significance [1-3]. In [1] a dynamic DNR based on HAS was proposed, which can determine annual feeder reconfiguration scheme considering switching costs and time-varying variables such as load profiles. In [2] a dynamic DNR method was proposed, which uses the optimal fuzzy C-means clustering method to classify the reconstructed period.

The above studies all assume that the DN is balanced so that the single-phase equivalent model is used for analysis. However, practical distribution systems are rarely balanced. Therefore, studying the unbalance DNR problem has important theoretical significance and engineering practice value. In [4], a reconfiguration model with comprehensive optimization objectives of minimizing three-phase unbalance factor and number of switching action was proposed, which based on the algebraic connectivity of graph theory is adopted to quickly remove infeasible solutions.

At present, there are three methods for dealing with DG uncertainty: interval number [5], fuzzy number [6], and random probability [7]. Compared with random probability and fuzzy number, interval number is not necessary to select parameters to deal with the uncertainty of DG output, as
long as it pays attention to the upper and lower bound information of the uncertain amount, it is more useful [8]. To address the aforementioned challenges, a dynamic DNR method is proposed, which takes the power loss, bus voltage deviation, and load balancing as objectives. The proposed method is divided into three part: ① The interval of DG output is predicted, and the prediction result is fed back to the power flow calculation in the form of affine number. ② The optimal DNR solution for each period is obtained through the improved multi-objective particle swarm optimization algorithm (MOPSO). ③ A reconfiguration period division method based on Mahalanobis distance is proposed to reduce the number of switching action until the optimal. Finally, the IEEE 34-bus system is used to verify the effectiveness of the proposed algorithm.

2. Treatment of uncertain factors
In this paper, the reconfiguration period is divided in hourly intervals. The DG output in each period is predicted and repeated φ times to obtain a predicted data set. The interval of DG output can be expressed as:

\[
\begin{align*}
\overline{P}_{d\theta, t} &= \mu_{d\theta} + 3\sigma_{d\theta} \\
\underline{P}_{d\theta, t} &= \mu_{d\theta} - 3\sigma_{d\theta}
\end{align*}
\]

(1)

where, \(\overline{P}_{d\theta, t}, \underline{P}_{d\theta, t}\) are the upper and lower interval value of DG output in period \(t\). \(\mu_{d\theta}, \sigma_{d\theta}\) are the mean and variance of the DG output data set in period \(t\).

The uncertainty of DG output is expressed in the form of the following affine number [8]:

\[ \tilde{P}_{d\theta, t} = \frac{1}{2} \left( \overline{P}_{d\theta, t} + \underline{P}_{d\theta, t} \right) + \frac{1}{2} \left( \overline{P}_{d\theta, t} - \underline{P}_{d\theta, t} \right) \cdot \varepsilon_{d\theta} \]

(2)

where, \(\tilde{P}_{d\theta, t}\) is the affine value of the DG output in period \(t\). \(\varepsilon_{d\theta} = [-1, +1]\) is the uncertainty factor affecting the DG output.

3. DNR Model
When considering the uncertain factors, the bus injection power is not a certain value, which is expressed in the form of affine number. Therefore, the objective function of DNR can be written as follows:

(1) Power loss

\[
\min f_1 = \tilde{f}_{\text{Ploss}} = \min \sum_{\Phi, k, i} N_{k} \left( \tilde{P}_{i, k, \Phi}^{\Phi} \right)^2 + \left( \tilde{Q}_{i, k, \Phi}^{\Phi} \right)^2 \left( \overline{U}_{i, k, \Phi}^{\Phi} \right)^2 \]

(3)

where, \(N_{k}\) is the number of branches, \(r_{k, \Phi}^{\Phi}\) is the resistance of phase \(\Phi\) of branch \(k\), \(\tilde{P}_{i, k, \Phi}^{\Phi}, \tilde{Q}_{i, k, \Phi}^{\Phi}\) are the affine value of active power and reactive power of phase \(\Phi\) of branch \(k\) in period \(t\). \(\tilde{U}_{i, k, \Phi}^{\Phi}\) is the affine value of voltage of phase \(\Phi\) at the end terminal of branch \(k\) in period \(t\). \(\Phi = A, B, C\).

(2) Bus voltage deviation

\[
\min f_2 = \Delta \tilde{U}^t = \max_{\Phi, i, k} \left| \frac{\tilde{U}_{i, k, \Phi}^{\Phi} - U_{\text{ref}}}{U_{\text{ref}}} \right|
\]

(4)

where, \(U_{\text{ref}}\) is the reference voltage of the bus. \(\tilde{U}_{i, k, \Phi}^{\Phi}\) is the affine value of voltage of phase \(\Phi\) of bus \(i\) in period \(t\).

(3) Load balancing

\[
\min f_3 = \text{SLBI} = \frac{1}{N_{k}} \sum_{\Phi} \sum_{k} \left( \frac{\tilde{S}_{i, k, \Phi}^{\Phi}}{S_{i, \Phi}^{\Phi, \text{max}}} \right)
\]

(5)
where, \( \tilde{S}_k^\Phi \) and \( S_{k_{\text{max}}}^\Phi \) are the affine value and upper limit of complex power of phase \( \Phi \) of branch \( k \) in period \( t \), respectively.

4. Improved MOPSO

MOPSO has been used to solve several multi-objective optimization problems, which is specifically designed to provide robust and scalable solutions. Therefore, MOPSO is more suitable for the optimization of multi-objective DNR problems. For more details of this algorithm, we refer to [9]. At same time, to improve the performance of the algorithm, we have made the following improvements:

1. Coding method

The traditional coding method for DNR is generally binary coding. We take into account the operation characteristics of the DN and use a decimal integer coding method [10]. The dimension of the solution is equivalent to the number of switching action. From each loop, the switches are selected to action to form a new topology. The encoding method can be expressed as:

\[
X = [X_{T1}, X_{T2}, ..., X_{Tn}]
\]

where, \( X \) is a set of switching action strategy, which also represents the position of the particle. \( X_{Tn} \) is the switch in the \( n \)-th loop.

2. levy flight

In order to prevent the MOPSO falling into a local optimal state during iteration, an archive \( F_e \) is created to record the difference entropy of each generation update. The difference entropy denotes the potential of the current population to find new solutions [9]. When the difference entropy does not change after a certain number of iterations, it means that the population has reached the optimal state or has fallen into a local optimal state. Therefore, in the current state, the particles vibrate by means of levy flight [11]. If a better solution is found, the current particle is updated. The step size of the flight obeys the levy stable distribution, it can be expressed as:

\[
L = X_{1}/X_{2}^{1/\beta}, \quad \beta \in (0, 2)
\]

where, \( X_1, X_2 \) are the Gaussian random number, \( X_1 \sim (0, \sigma_{X_1}), X_2 \sim (0, \sigma_{X_2}) \).

Therefore, the formula for particle position update can be written as:

\[
X_{i,d}^{T,n} = X + [L]
\]

where, \( X_{i,d}^{T,n} \) is the new solution for the \( d \)-th position of the \( i \)-th particle after the \( T \)-th iteration. \([ \] \) is an integer symbol.

The pareto solution set can be obtained by MOPSO, which contains many solutions. Therefore, the max-min method is used to select the compromise solution [12]. In this method, the objective function value is converted to membership. The problem of choosing the final solution is solved, which contains different dimensions and order of magnitude of multiple objective functions. And the subjective error caused by artificial selection is avoided.

5. Reconfiguration period division strategy

After the static reconfiguration in different periods is completed. Reconfiguration period division is the key step, which can effectively reduce the number of switching action. In this paper, the objective functions have three different orders of magnitude. Therefore, it is necessary to consider how to eliminate the impact of different orders of magnitude when the periods are divided. Therefore, a period division strategy based on Mahalanobis distance is proposed.

5.1. Mahalanobis distance

Mahalanobis distance was proposed by Indian statistician Mahalanobis to effectively calculate the similarity of two unknown samples of different orders of magnitude. The difference between Euclidean distance and Mahalanobis distance is that the latter takes into account the relationship between various features. The formula is as follows:
\[ d(x, y) = \sqrt{(x - y)^T C_{ov}^{-1} (x - y)} \]  \hspace{1cm} (9)

where, \( x \) and \( y \) are two random variables that follow the same distribution and the covariance matrix is \( C_{ov} \).

### 5.2. Reconfiguration period division

First, adjacent periods with the same topology are merged, and then the periods are divided again based on the Mahalanobis distance between the objective function values of the adjacent periods. The formula is as follows:

\[ d_{m,ij} = \sqrt{(X_i - X_j)^T C_{ov}^{-1} (X_i - X_j)} \]  \hspace{1cm} (10)

where, \( d_{m,ij} \) is the Mahalanobis distance of the objective function value in period \( i \) (\( i=1, \ldots, 24 \)) and \( j \) (\( j=1, \ldots, 24 \)), the smaller the Mahalanobis distance, the higher the similarity. \( X_i \) and \( X_j \) are M-dimensional vectors composed of the objective function values in the period \( i \) and \( j \).

The similarity for adjacent periods is as follows:

\[ \begin{cases} d_{m,ij} = 0 & \text{if } i = j \\ \Delta d_{m}^l = d_{m,ij} & \text{if } i > j \\ \nabla d_{m}^l = d_{m,ij} & \text{if } i < j \end{cases} \]  \hspace{1cm} (11)

where, \( \Delta d_{m}^l \) and \( \nabla d_{m}^l \) are the similarities of the front and back of the objective function of the period \( j \).

Second, equation (12) is used to unify the changes in the value of the objective function after dynamic DNR to the same order of magnitude, and to measure the result of the period division according to the target expectation. The target expectation can be got by:

\[ \eta_i = \frac{P^o_{\text{loss}} - P^n_{\text{loss}} + \Delta U^o - \Delta U^n}{\Delta U^o} + \frac{S^o_{\text{lbs}} - S^n_{\text{lbs}}}{S^o_{\text{lbs}}} \]  \hspace{1cm} (12)

where, \( P^o_{\text{loss}}, P^n_{\text{loss}} \) are the power losses before and after updating the topology, respectively. \( \Delta U^o, \Delta U^n \) are the bus voltage deviation before and after updating the topology, respectively. \( S^o_{\text{lbs}}, S^n_{\text{lbs}} \) are the load balancing before and after updating the topology, respectively.

Finally, compare \( \Delta d_{m}^l \) and \( \nabla d_{m}^l \), there are three ways to merge periods: ①If \( \Delta d_{m}^l > \nabla d_{m}^l \) and \( \eta_i \geq 0 \), the period \( j \) is merged with period \( j-1 \). ②If \( \Delta d_{m}^l < \nabla d_{m}^l \) and \( \eta_i \geq 0 \), the period \( j \) is merged with period \( j+1 \). ③If \( \Delta d_{m}^l = \nabla d_{m}^l \) and \( \eta_i \geq 0 \), the period \( j \) is merged with period \( j+1 \) and \( j-1 \). And so on, until the number of reconfiguration period is the smallest. If the above conditions are not met, the period \( j \) is independently a reconfiguration period.

The flowchart for obtaining the optimal solution of reconfiguration is shown in Fig.1:

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**Figure 1.** Flow chart of proposed DNR method
6. Case study
The proposed algorithm is developed in MATLAB. The diagram of the IEEE 34-bus system is shown in Fig.2. It is a 24.9kV, 34-bus unbalanced distribution system.

First, the adjacent periods are merged with the same structure. The results are shown in Table 1. According to method in Section 4.2, the final reconfiguration results are shown in Table 2.

![IEEE 34-bus system](image)

**Figure 2.** IEEE 34-bus system

| Period of time | Open switches | Period of time | Open switches | Period of time | Open switches |
|----------------|---------------|----------------|---------------|----------------|---------------|
| period 1-3     | S1S6S7S11S29 | period 5(11)   | S6S14S27S14S29| period 9(15-17)| S6S14S11S20S29|
| period 2(4)    | S6S16S7S14S20| period 6(12)   | S6S16S27S28S29| period 10(18-20)| S6S16S7S14S29 |
| period 3(5-8)  | S6S16S7S14S29| period 7(15)   | S6S16S12S32S20| period 11(21)  | S6S16S7S14S29 |
| period 4(9-10) | S6S14S11S29S29| period 8(14)   | S6S16S27S28S29| period 12(22-24)| S6S16S7S14S29 |

| Period of time | Open switches | Period of time | Open switches | Period of time | Open switches |
|----------------|---------------|----------------|---------------|----------------|---------------|
| period 1(1-3)  | S6S16S7S14S29| period 4(9-17) | S6S16S11S20S29| period 7(22-24)| S6S16S7S14S29|
| period 2(4)    | S6S16S7S14S29| period 5(18-20)| S6S16S12S14S29|                 |               |
| period3(5-8)   | S6S11S2S14S29| period 6(21)   | S6S16S7S14S29 |                 |               |

It can be seen from the comparison of the results in Table 1 and Table 2 that after using the period division strategy proposed in this paper, the number of reconfiguration periods is reduced from 12 periods to 7 periods. The number of switch actions has also been reduced from 25 to 10. The DNR results in the two reconfiguration periods and the base case are shown in Table 3. It can be seen that the reconfiguration strategy significantly improves the value of the objective functions.

**Table 3.** Objective function values in different situations

| Items          | Power loss (kW) | Voltage deviation /p.u. | SLBI      | Open switches |
|----------------|-----------------|-------------------------|-----------|---------------|
| Base case with DG | 212.471 2       | 0.103 2                  | 0.955     | S25 S26 S27 S28 S29 |
| 4              | 123.824 8       | 0.049 9                  | 0.421     | S6 S16 S17 S14 S29 |
| 12             | 78.623 2        | 0.041 1                  | 0.359     | S6 S14 S11 S20 S29 |
As can be seen from the Fig.3(a), the voltage distribution has been significantly improved when DG is connected. After reconfiguration, the bus voltage has been significantly improved. In Fig.3(b), the height of the curve represents the degree of pareto front update, and when the curve keeps approaching 0, it indicates that the algorithm converges. As can be seen from the Fig.3(b), the proposed method is converge in 120 iteration, and obviously better than the other algorithm.

7. Conclusions

Based on the three-phase imbalance modeling of the DN and considering the uncertainty of the DG output, this paper proposes a multi-objective reconfiguration scheme that can meet the optimal operation status of the DN. Aiming at the problem of period division after multi-objective reconfiguration, this paper proposes a period division strategy based on Mahalanobis distance and target expectation, which significantly reduces the number of switching action, and at the same time ensures that the DN operates in the best state.

8. Reference

[1] L. L. Pfitcher, D. P. Bernardon and L. N. Canha 2013 Intelligent system for automatic reconfiguration of distribution network in real time Electric Power Systems Research 97 pp 84-92
[2] M. H. Shariatkhah, M. R. Haghifam and J. Salehi 2012 Duration based reconfiguration of electric distribution networks using dynamic programming and harmony search algorithm Electrical Power and Energy Systems 41 pp 1-10
[3] M. Mosbah, S. Arif and R. D. Mohammedi 2017 Optimum dynamic distribution network reconfiguration using minimum spanning tree algorithm 5th International Conference on Electrical Engineering Boumerdes Algeria pp 1-6
[4] C. Peng, L. Xu and X. Gong 2019 Molecular evolution based dynamic reconfiguration of distribution networks with DGs considering three-phase balance and switching times IEEE Transactions on Industrial Informatics 15 pp 1866-1876
[5] Ding Tao, Cui Hanzhen and Gu Wei 2012 Uncertain power flow algorithm based on interval and affine operation Automation of Electric Power Systems 36 pp 51-55+115
[6] Sun Qiuye, Zhang Huaguang and Liu Zhaobing 2008 Study on fuzzy power flow calculation method and its convergence in distribution network Proceedings of the CSEE 28 pp 46-50
[7] K Kavousi-Fard A, Niknam T. and A. Khosravi. 2014 Multi-objective probabilistic distribution feeder reconfiguration considering wind power plants International Journal of Electrical Power & Energy Systems 55 pp 680-691
[8] M. Pirnia, C. A. Cañizares and K. Bhattacharya 2014 A Novel Affine Arithmetic Method to solve optimal power flow problems with Uncertainties IEEE Transactions on Power Systems 29 pp 2775-2783
[9] Hu Wang, Gary G. YEN and Zhang Xin 2014 Multi-objective particle swarm optimization algorithm based on Pareto entropy Journal of Software 25 pp 1025-1050

[10] J. Mendoza, R. Lopez and D. Morales 2006 Minimal loss reconfiguration using genetic algorithms with restricted population and addressed operators: real application IEEE Transactions on Power Systems 21 pp 948-954

[11] Y. Ling, Y. Zhou and Q. Luo 2017 Lévy Flight Trajectory-Based Whale Optimization Algorithm for Global Optimization IEEE Access 5 pp 6168-6186

[12] T. T. Nguyen, A. V. Truong 2017 Multi-objective electric distribution network reconfiguration solution using runner-root algorithm Applied Soft Computing 52 pp 93-108