Dynamic reconfiguration of distribution network considering
dynamic segmentation of time series load mean values

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Abstract. A novel dynamic reconfiguration model, in which the time interval segmentation is based on the time series load mean values, is proposed in this paper to deal with the access of distributed generation (DG), electric vehicle (EV) and the constraint of switch operation times. Firstly, a dynamic reconfiguration model with the lowest total daily cost is established, with the power outage loss cost considered. Secondly, the segmentation method of the equivalent daily load curve based on the dynamic segmentation of time series load mean values is proposed. Finally, the IEEE-33 nodes system is adopted to carry out the simulation, and calculation results are used to show the feasibility and effectiveness of the proposed segmentation method.

1. Introduction

Distribution network (DN) optimal reconfiguration can optimize power flow distribution, reduce grid loss, balance the load and improve power supply quality by optimizing the state of switches and changing the network topology, which is mainly divided into two aspects: static and dynamic. Static reconfiguration refers to the network optimal reconfiguration under a certain single-time period, in which the load state of system is kept constant. At present, the research on static reconfiguration of distribution network is relatively mature [1]. Dynamic reconfiguration is an optimal reconfiguration with considering the time variation characteristics of system state and the dynamic adjustment of network structure. In the reconfiguration process, not only the influence of load variation on network topology but also the constraint of number of switch operation times need to be taken into account [2-3]. The network reconfiguration of different system load state is carried out in reference [4-5], which reflects the time-varying characteristics of load in the actual operation of DN.

In recent years, DG, EV and other distributed resources have been widely applied in DN. In the actual operation of DN, the output power of DG and the charging power of EV are dynamically changing over time. Due to the uncertainty and randomness of DG and EV, only studying the static reconfiguration under a certain time period is no longer of practical significance to the operation of DN. The above discussion serves to highlight the importance of studying DN dynamic reconfiguration problem considering the time-varying nature of DG and EV, to ensure the safe, high quality and economical operation of DN. Under the constraints of switching action times, methods solving dynamic reconfiguration problem which considers randomness of DG and EV are as follows. Threshold value method is to merge the results of static reconfiguration of 24 time periods according to the defined index to satisfy the constraint of switch operation times. Various threshold value methods are employed to reconfigure the DN. In [6-9], power loss reduction index, mode switching minimum benefit index, a structure offset index, a dynamic loss parameter are introduced separately. The partition of time interval is finished according to the monotonicity of the changing trend of the
equivalent load curve of the system in [10-11]. With the increasing application of DG and EV, the equivalent load curve may fluctuate frequently, thus having multiple monotone intervals. The optimal fuzzy C-means clustering method is applied to classify the system state in a time interval according to the intrinsic similarity of load data in [12-14]. Time series reduction is needed after the fuzzy clustering of load data to realize the second stage division of time intervals. However, the clustering quality of fuzzy C-means clustering is affected by factors such as the number of cluster centers and parameter selection.

The dynamic reconfiguration of DN considering the time-varying nature of DG output, EV charging power is studied in this paper. The problem formulation is discussed in section 2, which includes the objective function and constraints of dynamic reconfiguration. The treatment of uncertainties and formation of equivalent load curve are introduced in section 3. The dynamic segmentation method of time series load mean values is introduced in section 4. The proposed reconfiguration method is carried out in the IEEE 33-bus distribution system in section 5. Finally, section 6 concludes this paper.

2. Problem formulations

2.1 Objective function

In previous studies, the objective function of dynamic reconfiguration is usually the minimum of power loss cost and switch operation cost during dynamic reconfiguration. However, according to the actual operation experience of DN, the reliability index should also be taken into account [15-17]. The objective function in this work is the lowest operation cost of DN within one day:

\[
\min f = \sum_{m=1}^{M} C_m \cdot P_{\text{loss},m} \cdot \Delta t_m
\]

where, \( M \) is the number of time segments of equivalent load curve; \( C_m, P_{\text{loss},m} \) and \( \Delta t_m \) are electrovalence, power loss and the duration of segment \( m \) respectively; \( N_s \) is the total number of switches; \( C_b \) is the cost of one switch operation; \( s_{m,j} \) is the state of switch \( j \) at segment \( m \) and when it is disconnected \( s_{m,j}=0 \) and otherwise \( s_{m,j}=1 \); \( C_{\text{ENS}} \) is the unit cost of power shortage; \( ENS_m \) is the index of unit time power shortage which characterizing the reliability of the network.

The index \( ENS_m \) of a certain network structure can be calculated as follows:

\[
ENS_m = \sum_{l=1}^{N_b} \lambda_l \cdot P_l \cdot t
\]

where, \( \lambda_l \) is annual failure rate of \( l \)th branch; \( N_b \) is total number of branches in DN; \( P_l \) is the total active power shortage caused by the failure of \( l \)th branch; \( t \) is the fault repair time of \( l \)th branch.

2.2 Constraints

The following several constraints should be taken into account when optimizing the dynamic reconfiguration model.

(a) Constraint of power flow equation

\[
AP = D
\]

where, \( A \) is node-branch correlation matrix of DN; \( P \) is line power flow vector; \( D \) is load demand vector.

(b) Constraint of node voltage

\[
U_{\text{min}} \leq U_i \leq U_{\text{max}}
\]

where, \( U_i, U_{\text{min}} \) and \( U_{\text{max}} \) are actual voltage amplitude, lower and upper range of voltage limits at node \( i \) respectively.

(c) Constraint of branch power transmission limit
where, \( S_l \) and \( S_{\text{max}} \) are power flow and the maximum allowable power flow at branch \( l \) respectively.

(d) Constraint of network topology
The configuration of DN should be kept radial in the process of dynamic reconfiguration, that is to say, there is no meshed network or island in the distribution system.

(e) Constraint of the operation times of switch

\[
N_j \leq N_{j_{\text{max}}} \quad N_{\text{total}} \leq N_{\text{total_{max}}} \tag{6}
\]

where, \( N_j \) is operation times of switch \( f_{\text{th}} \) within one day and \( N_{j_{\text{max}}} \) is its upper limit; \( N_{\text{total}} \) is total operation times of all switches within one day and \( N_{\text{total_{max}}} \) is its upper limit.

3. Formation of equivalent load curve
In this paper, the Beta distribution is used to describe the uncertainty of the active power output of wind and photovoltaic, and the probability density function is as follows:

\[
f(x) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1} \tag{7}\]

where, \( x = P/P_{\text{max}} \); \( P \) and \( P_{\text{max}} \) are active power output and its maximum value; \( \alpha \) and \( \beta \) are parameters of the Beta distribution.

The wind output power model used in this paper is as follows[18]:

\[
P_w(t) = \begin{cases} 0 \quad & 0 \leq v(t) < v_r \\ \frac{v(t)^{3/2} - v_r^{3/2}}{v_r^{3/2}} P_r \quad & v_r \leq v(t) < v_i \\ \frac{v_i^{3/2} - v_r^{3/2}}{v_r^{3/2}} P_r \quad & v_i \leq v(t) \leq v_o \end{cases} \tag{8}\]

where, \( P_w(t) \) is WT output power at moment \( t \); \( P_r \) is WT rated power; \( v(t) \) is wind speed of WT at moment \( t \); \( v_r, v_i \) and \( v_o \) are the rated wind speed, the cut-in wind speed and the cut-out wind speed respectively.

The photovoltaic output power model used in this paper is as follows:

\[
P_{p}(t) = n_{p} P_{p} \left[ \frac{R_{i}(t)}{R_{r}} \right] [1 + k(T(t) - T_r)] \tag{9}\]

where, \( P_{p}(t), R_{i}(t) \) and \( T(t) \) are PV output power, sunlight intensity and temperature respectively; \( P_{r}, R_{r} \) and \( T_r \) are unit rated power, rated sunlight intensity and rated temperature in standard scenario; \( k \) is power temperature coefficient; \( n_{p} \) is amount of PV units.

In this paper, electric vehicles are regarded as charging load under the random charging strategy. The charging power model in one day of EV is established mainly considering the daily mileage, the starting time of charging and the charging power. Interested readers can refer to reference [19-20], and we won’t explore it here.

The daily load curve, DG output power curve, EV charging curve are taken into account to form the equivalent load curve.

4. Time period dynamic segment method
A dynamic segment method based on the mean value of time series load is adopted to divide the equivalent load curve within one day.

4.1 Preliminary segmentation
The specific steps of preliminary segmentation of this method are as follows. First, the equivalent load is divided into 24 time periods equally, assuming that the load value of each node remains unchanged. Then load state can be expressed in matrix \( X = [x_{11}, x_{22}, \cdots, x_{n}](t=1, 2, \cdots, 24) \), where \( n \) represents the number of nodes and \( x_{ij} \) represents the complex load power of node \( i_{th} \) at time period \( t_{th} \).

Supposing that system load state is divided into \( M \) time intervals, it’s necessary to select (\( M-1 \)) time points in 24 time points as sequential segment points. After time period division, the load state matrix \( X \) can be described in matrix \( V = [v_1, v_2, \cdots, v_M] \). The load state of distribution system in \( m_{th} \)
sequential segment can be expressed in vector $v_m = [v_{m1}, v_{m2}, \cdots, v_{mn}]$, where $v_{mi}$ represents the complex load power of node $i_{th}$ at sequential segment $m_{th}$. The following equivalent load segment model is solved by genetic algorithm.

$$
\min f = \sum_{i=1}^{M} \sum_{j=1}^{N} |v_{ij} - v_{mj}| (m=1,2,\cdots,M)
$$

4.2 Dynamic correction
In general, the initial segment numbers $M_s$ of the equivalent load curve is given by experience. The above segment method is used to get the starting and ending time points and equivalent load power of each time interval. But the optimization result of dynamic reconfiguration under segment number $M_s$ may not satisfy the constraint of the switch operation times. It’s necessary to correct the number of segments dynamically. Comparing the total operation times of all switches $N_{total}$ with its upper limit $N_{totalmax}$:

(1) If $N_{totalmax} - N_{total} \geq 0$, output this optimal solution of dynamic reconfiguration directly.

(2) If $N_{totalmax} - N_{total} < 0$, correct $M_s = M_s - 1$ to decrease the segment number and the dynamic reconfiguration is carried out under new segment number. If the optimization result under new segment number is $N_{totalmax} - N_{total} \geq 0$, output the optimization result.

Fig. 1. Flow chart of dynamic reconfiguration

The flow chart of dynamic reconfiguration of DN considering demand response and dynamic time period division is shown in Figure 1. An improved genetic algorithm based on loop decimal coding is adopted to solve the dynamic reconfiguration model.

5. Case study
To verify the effectiveness the dynamic reconfiguration method proposed in this paper, the IEEE 33-bus distribution system is used for simulation and analysis, whose system structure is shown in figure 2. EV charging station, wind farm and photovoltaic unit are connected to the distribution system at node 5, 24 and 31 respectively.

Fig. 2. IEEE-33 nodes distribution system

5.1 Parameters in the model and case
1) The load data of each node in one day comes from reference [21].
2) Parameters and environmental data of wind turbine and photovoltaic unit are shown in Table 1 and Table 2 respectively. It is supposed that the power factor angle of wind power and PV is constant by adopting the reactive power compensatory equipment. The parameters of beta distribution are: \( \alpha = 2.767, \beta = 2.517 \) for the output power of wind [22], and \( \alpha = 0.85, \beta = 0.85 \) for the output of photovoltaic [23].

Table 1. Parameters of distributed generators

| Distributed generation | Parameter               | Value     |
|------------------------|-------------------------|-----------|
| Wind turbine           | Rated power             | 30 kW     |
|                        | Rated wind speed        | 12 m/s    |
|                        | Cut-in wind speed       | 3 m/s     |
|                        | Cut-out wind speed      | 24 m/s    |
| Photovoltaic unit      | Rated power             | 0.2 kWp   |
|                        | Rated sunlight intensity| 1 kW/m2   |
|                        | Rated temperature       | 25 °C     |
|                        | Power temperature       | −0.0045   |

Table 2. Environment data

| Time | Wind Speed (m/s) | Sunlight Intensity (KW/m²) | Temperature (°C) | Time | Wind Speed (m/s) | Sunlight Intensity (KW/m²) | Temperature (°C) |
|------|------------------|---------------------------|------------------|------|------------------|---------------------------|------------------|
| 0    | 9.8              | 0                         | 16               | 12   | 7.7              | 0.83                      | 18.4             |
| 1    | 9.2              | 0                         | 15.2             | 13   | 7.9              | 0.82                      | 18.6             |
| 2    | 9.1              | 0                         | 14.5             | 14   | 7.3              | 0.8                       | 18.6             |
| 3    | 8.5              | 0                         | 14.4             | 15   | 7.8              | 0.72                      | 19.5             |
| 4    | 8.3              | 0                         | 13.8             | 16   | 8.1              | 0.5                       | 19.2             |
| 5    | 8.4              | 0                         | 13.3             | 17   | 8.4              | 0.303                     | 18.6             |
| 6    | 7.3              | 0.2                       | 13.1             | 18   | 8.8              | 0.21                      | 18               |
| 7    | 8.8              | 0.315                     | 13.5             | 19   | 8.5              | 0                         | 17.3             |
| 8    | 7.4              | 0.5                       | 14.2             | 20   | 9.6              | 0                         | 17.1             |
| 9    | 8.2              | 0.68                      | 15.7             | 21   | 7.3              | 0                         | 16.9             |
| 10   | 8.6              | 0.735                     | 17.1             | 22   | 8.8              | 0                         | 16.3             |
| 11   | 9.1              | 0.79                      | 18.2             | 23   | 8.9              | 0                         | 15.8             |

3) The EV charging station connected to the network at node 5 provides charging services for 400 electric vehicles. The Monte Carlo method is used to obtain the charging power of EV under random charging strategy, as shown in figure 3.

Fig. 3. EV Charging power

5.2 Calculation result analysis
The equivalent daily load curve and segmentation method based on time series mean load are used to obtain the final segment result, which is shown in figure 4. In this paper, three other dynamic reconfiguration methods are adopted to verify the rationality and effectiveness of the dynamic reconfiguration method based on time series mean load. Method A is dynamic reconfiguration based
on time series mean load. Method B is threshold value method. Method C is dynamic reconfiguration based on the monotonicity of equivalent daily load curve. Method D is fuzzy C means clustering method. The calculation results of the above dynamic reconfiguration methods are shown in Table 3.

As we can see in Table 3, in the dynamic reconfiguration calculation results of method A, C, and D, the switching operation times and the total costs are significantly lower than that of method B. This indicates the advantage of pre-segmentation. Moreover, the threshold value method needs to calculate the static reconfiguration results of 24 time periods, so its computation burden is heavy.

Compared with the reconfiguration results of method C, the reconfiguration times, switching operation time and the total cost of method A are reduced 1 time, 2 times and 50.03 ¥ respectively. The problem of method C is that the load changes of each node in the DN are not taken into account, and the much fluctuation of the equivalent load curve leads to too many segments, which may result in breaking the constraints of switching operation times. Compared with the reconfiguration results of method D, the switching operation time and the total cost of method A are reduced 2 times and 24.96 ¥ respectively. When the number of segments applied to the dynamic reconfiguration is not the optimal number of cluster centers corresponding to the original load data, the quality of the clustering results will be poor and the result of the dynamic reconfiguration will be affected.

Table 3 Dynamic reconfiguration results comparison

| Methods   | Disconnected branch | Configuration times | Operation times | Total cost/ ¥  |
|-----------|---------------------|---------------------|----------------|---------------|
| Method A  | 0:00, 33/34/35/36/37 7:00, 25/33/34/36/36 9:00, 11/25/33/34/36 13:00, 11/25/33/34/36 15:00, 11/28/33/34/36 22:00, 11/28/33/34/36 | 3 6 | 1243.45 |
| Method B  | 24:00, 11/27/33/34/36 16:00, 11/28/33/34/36 22:00, 26/33/34/35/36 | 3 10 | 1296.73 |
| Method C  | 24:00, 25/33/34/35/36 7:00, 25/33/34/35/36 9:00, 11/25/33/34/36 13:00, 11/25/33/34/36 16:00, 7/11/28/34/36 22:00, 7/11/28/34/36 | 3 8 | 1268.41 |
| Method D  | 0:00, 25/33/34/35/36 9:00, 11/25/33/34/36 17:00, 11/28/33/34/36 22:00, 7/11/28/34/36 | 4 8 | 1287.01 |
6. Conclusion

In this paper, a dynamic reconfiguration method of distribution network based on time series mean time interval dynamic partition is proposed to solve the problem of dynamic reconfiguration of DN accessing with DG and EV and the difficulty of switching operation times constraints. The calculation results of the calculation example prove the rationality and effectiveness of the method. Compared with the existing several other segment reconfiguration methods of equivalent load curves, the dynamic partition method based on the time series load means can fully consider the time series characteristics of load information of each node in each time period. The time series reduction is not necessary, the calculation is simple, the solution is the starting time of each time segment and the system load state, and the number of segments can be dynamically adjusted according to the total switching operation times constraint.

References

[1] O. Badran, S. Mekhilef, H. Mokhlis, et al. Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies. Renew. Sust. Energ. Rev., 73, 854-867 (2017)

[2] H F Zhai, M Yang, B Chen, et al. Dynamic reconfiguration of three-phase unbalanced distribution networks. International Journal of Electrical Power & Energy Systems, 99, 1-10 (2018)

[3] A. Ajaja, F. D. Galiana. Distribution network reconfiguration for loss reduction using MILP[C]// IEEE Pes Innovative Smart Grid Technologies. IEEE Computer Society. 1-6 (2012)

[4] F. Flaih, X. Lin, M. Abd, et al. A New Method for Distribution Network Reconfiguration Analysis under Different Load Demands. Energies, 10, 4, 455 (2017)

[5] L Yin, J Yu. Dynamic reconfiguration (DR) of distribution network with multi-time periods. Proceedings of the CSEE, 22, 7, 44-48 (2002)

[6] J Yu, Z Wang, M Xu. Dynamic Reconfiguration of Distribution Network with Dividing Time and Considering Load Changes. High Voltage Engineering, 33, 9, 125-128 (2007)

[7] J Liu. Distribution networks dynamic optimization considering load changes. Relay, 32, 13, 15-19 (2004)

[8] W Wang, Y Zan. The application of quantum particle swarm optimization algorithm in multi-period dynamic reconfiguration of distribution network. Journal of Shaanxi Normal University, (2016)

[9] Y Li, G Wei, Y Ma, et al. Dynamic reconfiguration of active distribution network considering electric vehicles and distributed generations. Automation of Electric Power Systems, 42, 5, 102-110 (2018)

[10] X Fang, Z Guo. Optimal Time-Varying Coordinated Optimization in Distribution Systems. Transactions of China Electrotechnical Society, 21, 9, 31-36 (2006)

[11] Y Chen, W Tang, X Chen, et al. Tie switch allocation optimization based on dynamic segment of equivalent load-PV curve. Electric Power Automation Equipment, 35, 3 (2015)

[12] C Wang, Y Gao. Dynamic reconfiguration of distribution network based on optimal fuzzy C-means clustering and improved chemical reaction optimization. Proceedings of the CSEE, 34, 10, 1683-1691 (2014)

[13] J Zhou, L Que, L Wang, et al. Dynamic reconfiguration of distribution network based on improved optimal fuzzy C-means clustering and improved harmony search algorithm. Mechanical & Electrical Engineering Magazine, 32, 4 (2015)

[14] C Hou, R Wang. Dynamic reconfiguration of distribution network with distributed generation based on clustering. International Journal of Electrical Engineering, 24 (2017)

[15] M. R. Narimani, A. A. Vahed, R. Azizipanah-Abarghooee, et al. Enhanced gravitational search algorithm for multi-objective distribution feeder reconfiguration considering reliability, loss and operational cost. IET Generation Transmission & Distribution, 8, 1, 55-69 (2014)
[16] N. G. Paterakis, A. Mazza, S. F. Santos, et al. Multi-Objective Reconfiguration of Radial Distribution Systems Using Reliability Indices. IEEE Transactions on Power Systems, 31, 2, 1048-1062 (2016)

[17] Z. Ghofrani-Jahromi, M. Kazemi, M. Ehsan. Distribution Switches Upgrade for Loss Reduction and Reliability Improvement. IEEE Transactions on Power Delivery, 30, 2, 684-692 (2015)

[18] Z. Liu, Y. Chen, Y. Luo, et al. Optimized Planning of Power Source Capacity in Microgrid, Considering Combinations of Energy Storage Devices. Applied Sciences, 6, 12, 416-435 (2016)

[19] L. Tian, S. Shi, Z. Jia. A statistical model for charging power demand of electric vehicles. Power System Technology, 324, 11 (2010)

[20] J. Taylor, A. Maitra, M. Alexander, et al. Evaluation of the impact of plug-in electric vehicle loading on distribution system operations. Power & Energy Society General Meeting. (2009)

[21] H. Yang, Y. Peng, N. Xiong. A static method for distribution network dynamic reconfiguration. Relay, 37, 8, 53-57 (2009)

[22] X. Sun, C. Fang, F. Shen, et al. An integrated generation-consumption unit commitment model considering the uncertainty of wind power. Transactions of China Electro Technical Society, 32, 4, 204-211 (2017)

[23] G. Chen, P. Dai, H. Zhou, et al. Distribution System Reconfiguration Considering Distributed Generators and Plug-in Electric Vehicles. Power System Technology, 37, 1, 82-88 (2013)