Dynamic Reconfiguration Method of Distribution Network Containing Microgrid

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Abstract. The application of distributed power in the system has changed many characteristics of the traditional distribution network. Based on the consideration of the randomness of the load and the fluctuation and randomness of the output of the distributed generation, a new reconfiguration model of the distribution network with microgrid is established in this paper. Dynamic reconstruction is not a simple superposition of reconstructions in sub-periods. The influence of the number of switching operations on the operation mode between adjacent sub-periods and the overall optimality of the objective function must also be considered. The mathematical probability models of distributed generations and load are constructed in this paper. The dynamic reconfiguration is completed on the basis of probabilistic power flow. The objective function is calculated by stochastic power flow. The optimization algorithm is applied to the reconstruction process. The simulation results verify the effectiveness of the proposed model and algorithm in dynamic reconstruction.

Keywords: Dynamic Reconfiguration, Stochastic Power Flow, Random Variables, Optimization Algorithm

1. Introduction
Nowadays, microgrid technology continues to develop and become an important form of distributed power grid connection, which can smoothly switch between grid-connected and island mode. Microgrid is an effective way to solve the problem of distributed power grid connection. Due to the continuous development of microgrid technology, the fluctuation and randomness of distributed power output's impact on the distribution network becomes increasingly significant [1].

Dynamic reconfiguration needs to divide the total time period into different sub-time periods. In the same sub-time period, the power of the distributed power source must be dynamically matched with the load value. The reconstruction methods of distribution networks containing microgrids...
mainly focus on algorithm improvement [2]. The existing methods of distribution network reconstruction with microgrid mainly focus on the improvement of algorithms, which seldom consider the randomness, particularly the randomness of distributed power supply output [3].

This paper studies the dynamic reconfiguration of distribution networks containing microgrids, introduces uncertainty theory, considers random fuzzy factors to build a model for wind power and photovoltaic power prediction, using a static reconstruction and dynamic time segmentation reconstruction method.

2. Mathematical Model for Dynamic Reconstruction

2.1 Objective Function

The objective function takes the minimum active loss over the entire time period. The objective function can be expressed as:

$$\min \quad f = \min \left\{ P_{\text{loss}} = \sum_{i=1}^{M} |I_i|^2 r_i \right\}$$

where $M$ represents the sum number of branches. $I_i$ represents the current of the branch $i$. $r_i$ represents the resistance of branch $i$.

$$\overline{A}V_{\text{bus}} = Z_{\text{branch}}I_{\text{branch}}$$ (2)

Where $A$ represents the association matrix, $V_{\text{bus}}$ is the node voltage, $I_{\text{branch}}$ is the branch current, and $Z_{\text{branch}}$ is the branch impedance matrix. The total loss of the system can be obtained as:

$$P_{\text{loss}} = I_{\text{branch}}^T R_{\text{branch}} I_{\text{branch}} = V_{\text{bus}}^T A Z_{\text{branch}}^T R_{\text{branch}} Z_{\text{branch}} I_{\text{branch}} A V_{\text{bus}}$$

Delimit $T = A Z_{\text{branch}}^T R_{\text{branch}} Z_{\text{branch}} A$, then:

$$T = \begin{bmatrix}
\sum_{i=1}^{N} a_{1i} r_i & \sum_{i=1}^{N} a_{2i} a_{2i} r_i & \ldots & \sum_{i=1}^{N} a_{ni} a_{ni} r_i \\
\sum_{i=1}^{N} a_{1i} a_{2i} r_i & \sum_{i=1}^{N} a_{2i} r_i & \ldots & \sum_{i=1}^{N} a_{2i} a_{ni} r_i \\
\vdots & \vdots & \ddots & \vdots \\
\sum_{i=1}^{N} a_{ni} a_{2i} r_i & \sum_{i=1}^{N} a_{ni} a_{ni} r_i & \ldots & \sum_{i=1}^{N} a_{ni} a_{ni} r_i
\end{bmatrix}$$ (4)

Where $N$ is the number of buses, $a_{ij}$ is the element in the matrix, and $Z_i = r_i + j x_i$ is the impedance of branch $i$. The node voltage can be obtained using the following formula:

$$\begin{cases}
P_i = e_i \sum_{j=1}^{N} (G_{ij} e_j - B_{ij} f_j) + f_j \sum_{j=1}^{N} (G_{ij} f_j + B_{ij} e_j) \\
Q_i = f_j \sum_{j=1}^{N} (G_{ij} e_j - B_{ij} f_j) - e_j \sum_{j=1}^{N} (G_{ij} f_j + B_{ij} e_j)
\end{cases}$$ (5)

Where $V_i = e_i + j f_i$, $Y_i = G_{ij} + j B_{ij}$.

$$Y = A Y_{\text{branch}} A^T$$ (6)

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among them \( Y_{branch} = Z^1 \). Under a certain network topology, the correlation matrix \( A \) will stay consistent.

In summary, obtain the power loss as:

\[
P_{loss} = \sum_{j=1}^{N} \left[ \sum_{i=1}^{N} \sum_{k=1}^{M} \frac{d_k^j d_{kj} r_k s_k^2}{|Z_k|^2} \right]
\]  

(7)

3. Restrictions

3.1 Radial Topology Constraint

The structure of the micro-grid is generally radial, and the distribution network containing the micro-grid can be considered as multi-source radiation network.

\[
\sum_{k=1}^{M} |S_k| = N - d
\]  

(8)

Where \( d \) is the number of all balanced nodes.

All loads are uninterrupted, \( \text{rank}(A) = N - d \). At least one branch in each loop is open.

\[
\sum_{j=1}^{M} |S_j| \leq M_k - 1
\]  

(9)

Where \( M_k \) is the number of branches in loop \( k \).

3.2 Branch Current Limit

\[
l_j \leq l_{j}^{\text{max}}, \quad i = 1, 2, \ldots, n
\]  

(10)

Among them, \( l_j \) and \( l_{j}^{\text{max}} \) are the currents flowing on branch \( i \) and their maximum values, respectively.

3.3 Node Voltage Limit

\[
U_j^{\text{max}} \leq U_j \leq U_j^{\text{min}}, \quad i = 1, 2, \ldots, n
\]  

(11)

Among them, \( U_j \) is the voltage of node \( i \). \( U_j^{\text{max}} \) and \( U_j^{\text{min}} \) are the upper and lower limits of the voltage, respectively.

3.4 Distributed Power (Dg) Capacity Limits

\[
P_{\text{Dg}}^{\text{min}} \leq P_{\text{Dg}} \leq P_{\text{Dg}}^{\text{max}}
\]  

(12)

\[
Q_{\text{Dg}}^{\text{min}} \leq Q_{\text{Dg}} \leq Q_{\text{Dg}}^{\text{max}}
\]  

(13)

In the formula: \( P_{\text{Dg}} \), \( P_{\text{Dg}}^{\text{max}} \) and \( P_{\text{Dg}}^{\text{min}} \) are the active power of the source \( i \) and its upper and lower limits, \( Q_{\text{Dg}} \), \( Q_{\text{Dg}}^{\text{max}} \) and \( Q_{\text{Dg}}^{\text{min}} \) are reactive power of the source \( i \) and its upper and lower limits, respectively.
4. System Stochastic Model

The random variables in the power system are mainly divided into continuous and discrete types. Therefore, fuel cells and lines are discrete random variables [4].

4.1 Stochastic Model of Wind Power System

Due to the fluctuation of the wind speed, the output of wind turbine is random. The Weibull probability density function of the wind speed is:

\[
f(v) = \frac{k}{c} \left( \frac{v}{c} \right)^{k-1} \exp \left[ -\left( \frac{v}{c} \right)^k \right]
\]  

(14)

Where \( v \) is wind velocity, \( k \) is Weibull distribution shape parameter. \( c \) is Weibull distribution scale parameter. Two parameters can be approximated by the average value of wind speed with standard deviation.

4.2 Stochastic Model of PV System

As photovoltaic system will be affected by the intensity of sunlight, it will show volatility. The solar light intensity meets the beta distribution, and the probability density function is:

\[
f(r) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \left( \frac{r}{r_{\max}} \right)^{\alpha-1} \left( 1 - \frac{r}{r_{\max}} \right)^{\beta-1}
\]  

(15)

Where \( r \) is the light intensity, \( r_{\max} \) is the peak value of the light intensity within a given period of time. \( \alpha \) and \( \beta \) are parameters representing shape.

4.3 Load Stochastic Model

In different time periods, the load fluctuations of the system are time-varying and random. Generally, the normal distribution is used to characterize the load changes. The probability function is:

\[
f(P) = \frac{1}{\sqrt{2\pi}\sigma_P} \exp(- \frac{(P - \mu_P)^2}{2\sigma_P^2})
\]  

(16)

\[
f(Q) = \frac{1}{\sqrt{2\pi}\sigma_Q} \exp(- \frac{(Q - \mu_Q)^2}{2\sigma_Q^2})
\]  

(17)

Where \( \mu_P \) is the mean of active power, \( \mu_Q \) is the mean of reactive power, \( \sigma_P^2 \) is the variance of active power, \( \sigma_Q^2 \) is the variance of reactive power.

5. Stochastic Flow

The stochastic power flow considers the uncertainty of the load, as well as the randomness of power in distributed generation. The traditional power system power flow equation is [5]:

\[
\begin{align*}
P_s &= V \sum_{j \in i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\
Q_s &= V \sum_{j \in i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij})
\end{align*}
\]  

(18)
6. Optimization Algorithm
The immune clonal selection and differential evolution is applied to reconfiguration, which can enhance the local search of the problem while taking into account the global search.

Algorithm flow:
1. Form the original data input, including node information and branch information, and set the initial control parameters of the algorithm.
2. The initial population is set by the initial state parameters of the system. Get the scale of the system n, clone radius r, high frequency coefficient of variation r.
3. Calculate the value of the objective function. Monte Carlo random power flow is used to determine whether constraints of system operation state and topological relationship are violated.
4. Monte Carlo random power flow, antibody clustering, clone amplification, high frequency mutation and other operations are carried out for the antibody group.
5. Repeat the calculation until the network loss is no more than 10% and the iteration end condition is met.

7. Analysis of Simulation Examples
The IEEE-33 node distribution network system is adopted [6-7]. Three wind turbines are connected at nodes 9, 14 and 18, with the rated power of 100kW. At nodes 20, 26 and 30, 10 solar photovoltaic module arrays are connected, and the rated power of the PV module is 100kW. The load of each node in the system at each time is obtained according to the daily load curve. The number of samples taken is 1000. The initial data is calculated by stochastic power flow. Parameter setting: maximum number of iterations, initial antibody population n = 50, number of clustering centers M = 5, selection rate, cell clone radius, high frequency coefficient of variation r = 0.6, antibody supplement coefficient, control parameter f=0.02. The probability density distribution curve of branch power flow and node voltage is obtained as follows:

![Figure 1. IEEE-33 node](image1)

![Figure 2. The curve of active power distribution](image2)

![Figure 3. The curve of voltage probability density in node 31](image3)

It can be seen from the figure nodes 16 to 22, the transmission of active power on the feeder is large, and the voltage level of node 31 is relatively low. Due to the output of distributed power supply,
the power transmission between feeders is reduced. As a result, system losses are reduced.

Table 1. The comparison of network loss

| Time          | Open branch | Network loss before reconfiguration | Network loss after reconfiguration |
|---------------|-------------|-------------------------------------|-----------------------------------|
| 1:00-6:00     | 3-4,12-13,19-20,7-20,8-14 | 198.42                             | 125.37                           |
| 7:00-9:00     | 9-10,30-31,7-20,24-28,31-32 | 89.6                               | 57.21                            |
| 10:00-15:00   | 9-10,26-27,31-32,7-8,12-13 | 87.93                              | 69.75                            |
| 16:00-20:00   | 8-14,2-3,31-32,7-20,26-27 | 95.36                              | 80.22                            |
| 21:00-24:00   | 2-3,11-21,8-14,24-28,31-32 | 156.23                             | 132.75                           |

8. Conclusion
In this paper, load output and load randomness are considered. The corresponding random probability model is established. Through the stochastic power flow calculation of the system, the optimization algorithm is used for dynamic reconstruction calculation. The simulation results show that the network loss and voltage quality are significantly improved after optimization. Considering the randomness has an important influence on the calculation.

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