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Distribution Network Loss Calculation and Reactive Power Optimization Loss Reduction Analysis

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Abstract: Traditional deterministic power flow and static reconfiguration methods can not take into account the influence of uncertain factors in power grid. Therefore, a multi-objective dynamic reconfiguration method based on probabilistic power flow considering the randomness of load and DG is proposed. The probabilistic model of distributed generation (DG) output and load is established, and the probabilistic power flow is calculated by using semi invariants and gram - Charlie series. The structure of distribution network is diverse and the topology is complex. The access of distributed generation (DG) makes the structure of distribution network more complex. In the complex distribution network structure, once a fault occurs somewhere, if it can not be quickly and accurately implemented, it will cause a large area of power failure and bring huge economic losses. After the emergency repair, if the network structure is not recombined, there will be problems such as low power supply reliability and operation efficiency of the distribution network. Therefore, it is of great significance to study the emergency repair and recovery strategy for complex distribution network with multiple faults.

1. Introduction

Distribution network reconstruction can be divided into static reconstruction of single time section and dynamic reconstruction of multiple time section. The static reconstruction method can only obtain the optimal network structure under a certain state of the system, ignoring the changes of the system state, so it is not practical. The dynamic reconstruction mode has higher practicability because it can dynamically adjust the network structure according to the change of system state [1-2].

The variation of power load is random, so the power flow distribution of the system is also random, and it is further intensified with the access of DG. The traditional system analysis method based on the deterministic power flow cannot describe the randomness, so it is of great significance to study the distribution network reconfiguration strategy based on the probabilistic power flow.

In recent years, domestic and foreign researchers have done a lot of research on distribution network reconfiguration, but most of them focus on static reconfiguration, while dynamic reconfiguration is less. Literature [3] takes improving DG permeability as the goal to carry out dynamic network reconstruction, but the shortcoming is that the fluctuation of power load is ignored. Literature [4] regards the DG output in different time periods as a fixed value, carries out network reconstruction and optimizes the DG capacity in the case of considering the fluctuation of load, but the shortcoming is that the randomness of DG output is not considered. The uncertainty of load and DG output is considered by dividing them into multiple scenarios, but this method is only suitable for static refactoring. In literature [5], load characteristic indexes were used to cluster the load and determine the reconstruction period. Dynamic reconstruction was carried out with the goal of network loss and load balance, but the voltage quality of the system was not optimized, and the voltage in some areas might not reach the standard.

In view of the limitation of the emergency repair and recovery strategy based on the instantaneous load value at the time of fault occurrence, this paper considers the characteristics of the time-varying load and the long duration of emergency repair and recovery, and studies the multi-fault emergency repair sequence of distribution network and the optimization of network reconstruction after emergency repair and recovery. In the stage of emergency repair and recovery, the maximum load value after emergency repair is taken as the goal; In the reconfiguration stage after fault recovery, a binary particle swarm optimization (PSO) algorithm was used to solve the model, aiming at minimizing the weighted sum of voltage offset and network loss. In the solution, rush repair and recovery alternate and cooperate, cycle and reciprocate, and influence each other. In addition, in view of the low efficiency of power flow calculation and optimization due to the existence of many infeasible solutions in the algorithm population, a node layered power flow calculation method based on particle position vector and a particle swarm optimization algorithm based on loop network coding are proposed.

2. Distribution Network Fault Recovery Model

Usually, the fault repair and recovery strategy is solved according to the load value of the node access at the moment when the fault occurs in the distribution network. However, in practice, the load of the distribution network is time-varying, so it is obviously limited to calculate the multi-fault repair and recovery strategy of the distribution network by ignoring the time-varying load. Aiming at this problem, this paper establishes a solution model considering the time-varying characteristics of load. Solving emergency repair order, according to the failure in recovery after emergency recovery value to determine the repair order, each time to not only repair recovery failure recovery in the value of the biggest one failure to repair, after the repair immediately closed the fault branch, to network loss and voltage offset of the weighted and minimum as the target for the reconstruction of the space truss optimization [6].This alternates and circulates until all failures are repaired, and the order and recovery strategy of the failures are obtained. The emergency repair and recovery model considering the time-varying load is closer to the reality, and the strategy is more accurate, which has the global optimum in the true sense.

2.1 Load Characteristic Model

This paper mainly considers the time-varying characteristics of load, and the load shows different time-varying characteristics in different seasons and different periods [7].In this paper, the daily load prediction of distribution system is carried out and the daily load curve of each node of distribution network is obtained. Then, the daily load curve is integrated to obtain the load value of each node in each period. The time-varying model of the load is expressed $I_{l\cdot t} \leqslant I_{l\max} \quad l=1,2,\cdots,n$

$$F_i(t)=\int_t^{t+1} f_i(x)\mathrm{d}x, t=0,1,\cdots,23 \quad (1)$$

Where,F_i (t) is the load value of node I in time period t; $F_i(x)$ is the load curve function of node i.

In this paper, the duration of each time period is set as 1h, and the expected rush repair and repair duration of each fault point is set. The corresponding time period is determined according to the time when the fault occurs and the repair duration, and then the time load of the node is obtained.

2.2 The Objective Function

Assuming that the repair time of each fault has been given, in the stage of multi-fault emergency repair and recovery, the maximum restored load value after the failure is taken as the objective function [8], and its model is

$$\max f_1=\sum_{i\in D_n} k_{i,t} w_i F_{i,t} \quad (2)$$

In the formula, $k_{i,t}$ is the charged state of load node i in time period t, 1 is charged, 0 is power loss; w_i is the weight of importance grade of load node i; $f_{i,t}$ is the load amount of load node i in time period t; D_n is the collection of load nodes in non-fault power loss area [9].

2.3 The Constraint

1) In order to meet the requirement of open loop operation of the distribution network at any time period, the network topology should meet the radial shape [10] :

$$g_k \in G_k \quad (3)$$

In the formula, g_k is the current distribution network operation structure; G_K is the collection of all radial structures of the distribution network.

2) In order to ensure the safe and reliable operation of the distribution network in the process of fault recovery, the branch current shall meet the capacity constraint:

(4)

In the formula, $I_{l\cdot t}$ is the current flowing through line l at time period t; I_{Lmax} is the maximum current flowing through line l; n is the number of lines.

In order to ensure the safe and reliable operation of the distribution network in the process of fault recovery and to avoid node voltage exceeding the limit, the node voltage shall meet the following constraints:

$$U_{i\min} \leqslant U_{i\cdot t} \leqslant U_{i\max} \quad i=1,2,\cdots,n \quad (5)$$

In the formula, U_{imin} and U_{imax} are the lower limit and upper limit of node voltage respectively; $U_{i\cdot t}$ is the voltage amplitude of node I in time period t, and n is the number of nodes.

In order to make the power balance of the distribution network meet the following constraints at any time:

$$P_{i,t}-V_{i,t}\sum_{j=1}^{n} V_{j,t}(G_{ij}\cos\delta_{ij,t}+B_{ij}\sin\delta_{ij,t})=0 \quad (6)$$

$$Q_{i,t}-V_{i,t}\sum_{j=1}^{n} V_{j,t}(G_{ij}\cos\delta_{ij,t}+B_{ij}\sin\delta_{ij,t})=0 \quad (7)$$

In the formula, $Q_{i,t}$, P_i and t respectively represent the reactive power and active power of the injection node i during the fault recovery period of t; G_{ij}, B_{ij} and $\delta_{ij.t}$ represent the conductance, suscance and voltage phase Angle difference t between two nodes i and j respectively. n is the number of system nodes; $V_{i,t}$, V_j and t are voltage amplitudes of node i and node j in the fault recovery period t respectively.

3. Improved Immune Algorithm to Solve Dynamic Reconstruction Model

3.1 Immune Algorithm Improvement

Dynamic network reconstruction of distribution network has the characteristics of large scale, high dimension and high timeliness. There are several serious problems in the traditional single-population serial str ucture immune algorithm and conventional evolutionary algorithm when dealing with such large-scale complex problems :(1) the computation time is too long;(2) In the selection process, antibodies containing key genes are easy to be lost, resulting in a serious decline in population diversity, and the search process falls into local optimization;(3) The local search efficiency of dominant individuals is low and fast convergence cannot be achieved.

In order to solve these problems, a new multi-population parallel immune algorithm was proposed by referring to the mechanism of cell interaction and immune memory in biological immunity and the idea of coarse-grained model in parallel genetic algorithm. This paper mainly designs the algorithm from three aspects: the structure of the algorithm, the evolutionary strategy of subpopulations and the way of information interaction between populations.

3.1.1 Subpopulation Evolutionary Strategy

(1) The dominant subpopulation, whose main role is to carry out local search to achieve rapid convergence of the dominant individuals. According to the “concentration” and “symmetry” properties of the Gaussian distribution function, an adaptive Gaussian mutation operator is designed to conduct local search on the dominant individuals. The Gaussian distribution function is as follows:

$$G = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(t-u)^2}{2\sigma^2}\right) \quad (8)$$

Where, expectation u is the starting point and variance σ is the variation rate.The local optimal threshold V_T, the stasis algebra V_G, and the $V_G \in [0, V_T]$ are set. When the optimal affinity increase of offspring is less than a certain value, the population evolution is considered to be stagnant. The stasis algebra is added by one, that is, if $f(i+1)_{max} - f(i)_{max} < \delta$, V_{G+1}, otherwise V_G is zero.

Definition of variation rate:

$$\sigma = \sigma_{\max} \cdot \exp\left(-\frac{V_T - V_G}{V_T}\right) \quad (9)$$

Adaptive Gaussian mutation operator:

$$M_i' = M_i + \eta e^{-f_i/f_{i\max}} \cdot (X_{\max} - X_{\min}) \cdot G \quad (10)$$

Where M_i is the antibody before mutation; η is the regulation coefficient; f is antibody affinity; X_{min} and Xmax are the head and tail boundaries of the antibody.

In the search process, the mutation rate adaptively adjusts with the evolution of the population. In the evolutionary stage, σ is small, and the variation concentrates in a small area to realize the refined search for the dominant individuals. When the evolutionary process tends to stagnate, σ increases gradually, expanding the search space.

(2) Common subpopulation, whose main function is to improve the global search ability and avoid falling into local optimum.An important way to do this is to increase population diversity, with crossover (antibody interactions) and high-frequency mutations being the main ways to increase diversity.

Antibody crossover operator is designed to realize the information exchange of antibodies:

$$N_i' = N_i + \gamma(N_j - N_i) \quad (11)$$

Where N_i is the pre-mutation antibody; N'_i is the mutant antibody; N_j is an antibody in the neighborhood. γ is crossover rate γ = 1-exp (-C_i/F_i); C_i is the antibody concentration, which has a greater crossover rate to the individuals with high concentration and low affinity.

The hypermutation operator is used to carry out the mutation operation on the population, and the mutation rate p is:

$$p(N_i) = \exp(-\lambda f_i / f_{\max}) \quad (12)$$

Where F_i is individual affinity; F_{max} is the current optimal affinity; λ is the proportional regulation coefficient. The hypermutation operator can effectively improve the population diversity by carrying out large probability variation on the individuals with medium and low affinity.

3.1.2 Subpopulation Information Interaction Mode

In order to give consideration to the global and local search ability of the algorithm, the two subpopulations need to exchange information and share good information in the evolutionary process, so as to correct the evolutionary direction.The memory population J is set to realize the information exchange among subpopulations.

The implementation steps are as follows: (1) After the two subpopulations run independently for n generations, the individuals are sorted according to the affinity degree and divided into three levels: 1, 2 and 3; (2) The top 15% of individuals in grade 1 of the two populations and 10% of individuals in grade 2 and 3 of N population were randomly selected to replace the same number of antibodies with low affinity in the memory population to update the memory population; (3) For population N, after excluding the population autoantibodies, t antibodies were randomly selected from the memory population to replace the t antibodies with the worst affinity in the subpopulation. For population m, after excluding the population autoantibodies, the optimal k antibodies were selected from the memory population to replace the k antibodies with the worst affinity in the M population to complete the information interaction among subpopulations.

3.2 Dynamic Reconfiguration Model of Distribution Network Based on Improved Parallel Immune Algorithm is Solved

(1) Coding. The coding method in literature [7] is adopted to divide the distribution system into several ring networks, and each ring network has only one switch to

disconnect, which ensures radial topological constraints and greatly reduces the number of infeasible solutions.

(2) Population initialization and affinity calculation. Set the population size as K, the maximum number of iterations T, uniformly distribute to generate the initial population, and take the reciprocal of the normalized objective function as the affinity:

$$F=1/F^* \tag{13}$$

(3)The size of memory population was j. The affinity of the initial population was calculated, and m antibodies with higher affinity were composed of dominant subpopulation M, and the remaining K-m antibodies were composed of common subpopulation N.j antibodies were uniformly extracted to form a memory population.

(4) Determine whether the termination condition of the algorithm is met. If so, the output will be achieved. If not, the following steps will be continued.

4. The Example Analysis

4.1 Related Parameter Setting

The IEEE 33-node system is taken as the object, and the network structure is shown in Figure 1, in which the line and load prediction data are quoted from the literature [11]. The total load of the system is 3830kW + J2215$kvar$, the reference value V_B = 12.66 KV and S_B = 10 MW. Predicted values of wind speed and irradiation intensity in different periods refer to literature [12].Nodes 7, 21 and 28 are connected to PV, with an access capacity of 3× 320 kW.16. 25 Access fan with access capacity of 2× 250 kW.

Related parameters of fan model P_{rw} = 0.125 MW, V_{ci} = 4 m/s, V_{co} = 24 m/s, V_r = 14 m/s, K= 1.99, C=9.49, power factor 0.89. Related parameters of photovoltaic model η = 15%, R_{max} = 310 W/m^2, α = 0.85, β = 0.85. The power of load point I follows a normal distribution with expectation μ_i= S_i variance σ_i= 0.1S_i.

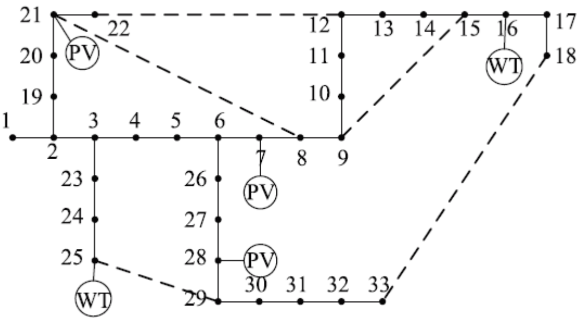

Fig.1 System Structure Diagram

4.2 Period Division

Classical PAM clustering and SA-PAM clustering were used to cluster load sample data under the same clustering number, and the results were shown in Table 1.

Table 1 Comparison of Clustering Results

Category	Clustering number	Number of convergence	Mean complex class inner distance S (K)	Average running time per second
The PAM clustering	20	12	0.435	2.729
SA-PAM	20	17	0.214	6.367

clustering				

The results show that the proper acceptance of the “bad solution” mechanism in simulated annealing can prolong the computation time, but effectively improve the probability of convergence and the clustering quality. The time period partition problem does not require high speed, so it is desirable to sacrifice a certain speed to improve the quality of operation.

The loss function curve method in reference [13] is used to determine the optimal number of segments, and the loss function S (K) is defined as the comprehensive class inner distance:

$$S(K) = \sum_{i=1}^{K} \sum_{p \in C_i} Dis(C_i, p) \qquad (14)$$

In the formula, Ci is the ith cluster center, and P is the non-central point in the class. The value range of the given number of segments is [14,15]. The loss function under different number of segments is calculated and fitted, and the curve of the loss function is shown in Figure 2. Determine the optimal number of segments as 5.

The results of SA-PAM clustering showed that the five clustering center points were 3, 8.5, 14, 18.5, 22, respectively. According to the division rules mentioned in Section 5.2, the result of time period division is shown in Fig. 3.

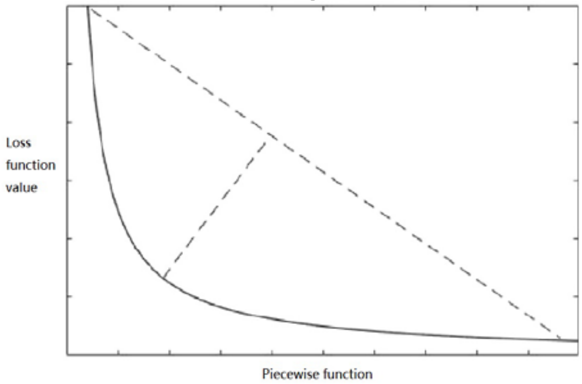

Fig.2 Loss Function Curve

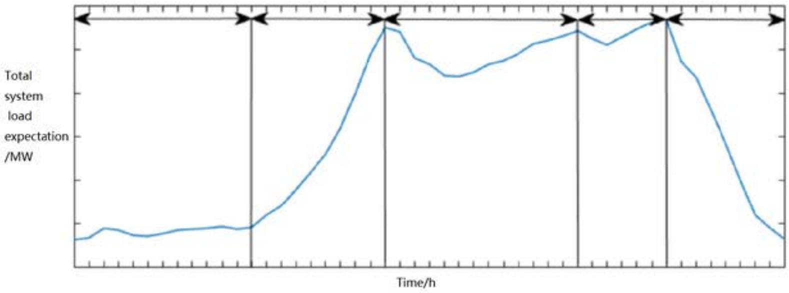

Fig.3 Results of Time Period Division

4.3 Validation of the Improved Immune Algorithm

Taking T_2 time period reconstruction calculation as an example, the proposed improved parallel immune algorithm is compared with the traditional clone immune algorithm. The population size is 100 and the maximum iteration number is 50. The parameters of the improved parallel immune algorithm are as follows: U = 0, maximum mutation rate σ_{max} = 0.05, V_T = 5, cloning coefficient 0.9, Gaussian mutation operator regulation coefficient η = 0.2, crossover probability γ = 0.85, supermutation operator proportionality coefficient λ = 0.5, subpopulation size M = 20, N = 80. Run Algebra 10 independently. The algorithm iteration process is shown in Figure 4.

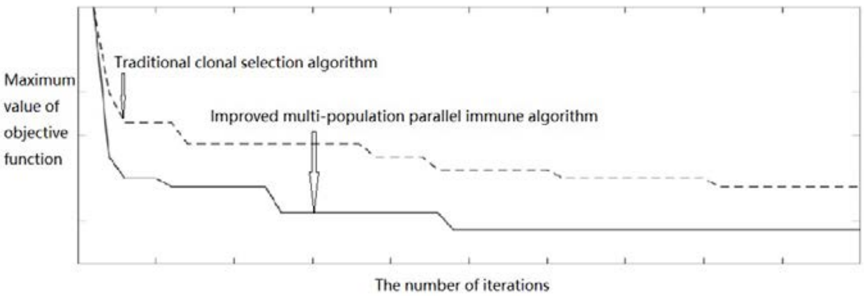

Fig.4 Comparison of Iterative Processes of the Algorithm

It can be seen from the figure that the improved parallel immune algorithm converges 24 times and the optimal objective function value is 0.481; the traditional clonal immune algorithm converges 41 times and the optimal value is 0.573. For the solution of distribution network reconfiguration, the improved multi-population parallel structure of parallel immune algorithm can improve the convergence speed of the algorithm. On the other hand, the dominant individual local search strategy can improve the convergence speed and the solution quality. Therefore, compared with the traditional immune algorithm, the improved parallel immune algorithm has more advantages in solving the problem of distribution network reconfiguration.

The voltage before and after reconstruction at 33 nodes in T_2 period is taken as an example to verify the effectiveness of the algorithm. The voltage probability distribution is shown in Fig. 5.

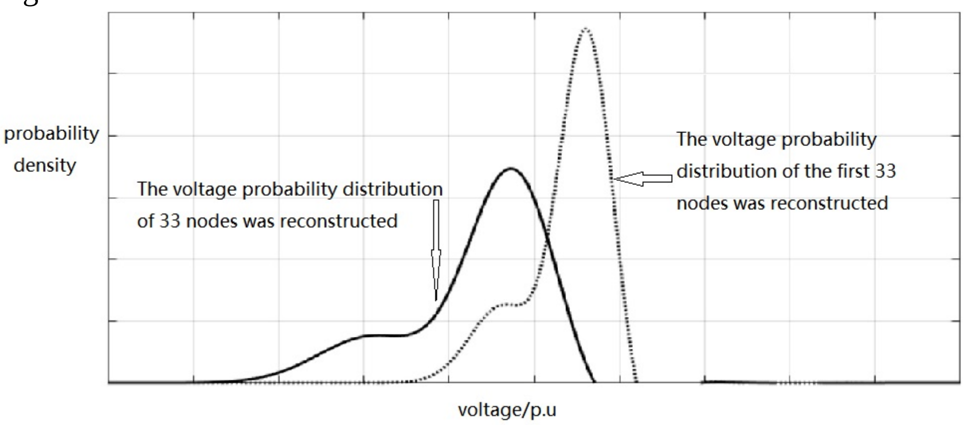

Fig.5 33 Probability Distribution of Node Voltage

According to the simple calculation in Fig. 1, the voltage out-of-limit probability before reconstruction is 0.0231, and the voltage expectation is 0.963.After the reconstruction using the improved immune algorithm, the out-of-limit probability of node voltage decreased to 0, and the voltage expectation increased to 0.978.The effectiveness of the improved immune algorithm in the calculation of distribution network reconfiguration is verified.

4.4 Comparison of Reconstruction Results

As can be seen from Table 1, after the dynamic reconstruction of the distribution network, the system voltage overlimit probability drops to 0, the situation of network loss expectation and non-reconstruction decreases by 23% compared with the same period last year, and the voltage offset level decreases by 25%. Effectively improve the operation of distribution network.

Several different reconstruction strategies were compared, and the results were shown in Table 3, of which single reconstruction strategy was referred to [16].

Table 2 Comparison of Several Refactoring Strategies

	Average net loss expectation	System voltage overlimit probability	System average voltage deviation	Switching times
Don't refactor	127.9	0.0293	0.0382	0
A single refactoring	112.1	0.0205	0.032	6
Full time reconstruction	86.6	0	0.023	48
Dynamic reconfiguration	97.1	0	0.0287	22

By comparison, it can be seen that the single reconstruction method has less switching operation times, but the network loss and voltage conditions have not been greatly improved, so the reconstruction effect is not good. Compared with dynamic reconstruction, full-period reconstruction improves both the network loss and voltage indexes, but the increase is small. However, the number of switching actions in full-period reconstruction increases sharply, leading to higher switching costs. Considering various factors, the dynamic reconstruction in a specific period has a relatively good effect.

5. Conclusion

A dynamic reconfiguration method of distribution network based on probabilistic power flow and SA-PAM clustering is proposed. The stochastic characteristics of distribution networks with DG are considered by probabilistic power flow calculation. According to the load characteristics at different times, the time axis was divided into clusters to determine the reconstruction period, so as to avoid the frequent switch action caused by the reconstruction of the whole period.An improved multi-population parallel immune algorithm is proposed to solve the problem of slow solving speed and low efficiency of dynamic reconstruction model.

The simulation results show that the proposed distribution network reconfiguration method can effectively reduce the network loss expectation and voltage overlimit probability, and improve the economy, security and power quality of distribution network operation.

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