Chapter 68
The Application of Hybrid Immune Algorithm in Distributed Generation Distribution Planning

Chun Li and Xiaoliu Shen

Abstract This paper focuses on how to determine the location and the constant volume of distributed generation. Firstly, we establish the multi-objective distributed generation planning model for the minimum network loss, minimum average deviation of the node voltage and the minimum total investment cost. Then the hybrid immune algorithm (HIA) is used in the optimization computing of distributed power distribution planning. In order to improve the convergence speed, the clonal selection algorithm has been modified to adjust the circumstance. Also the PSO algorithm is introduced in the calculation of high-frequency variation. The improved algorithm overcomes the problem that the calculation of the latter part is easy to fall into local convergence. The case study applies the HIA to IEEE 33 nodes test system, the simulation result shows that the HIA is effective and feasible in the problem of distributed generation distribution planning.

Keywords Hybrid immune algorithm · PSO · Distributed generation · Multi-objective optimization

68.1 Introduction

In recent years, along with the implementation of smart grid strategy, distributed generation has been recognized worldwide. Market penetration is still very low, but the field is undergoing rapid growth. Therefore, actively studying the distributed energy development model in the smart grid environment is of great

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significance for the future large-scale development of distributed energy and eases the energy crisis [1].

The combination of main power grids and distributed power generation is recognized as the most important way which is able to save the investment, reduce energy consumption and improve power system reliability and flexibility [1]. When a large number of distributed generations in the planning scheme, a large number of random changes in the power system appears, and improves the complexity of the system [2]. To address this issue, in this paper, the improved clonal selection algorithm is applied to optimize the distribution network, trying to establish a comprehensive, robust distribution network system.

68.2 Distributed Generations

Distributed generation (DG) is a small unit which is dispersed installed on the user side, both independent of the public grid directly provide electrical power for the around user, and access to distribution networks with the public grid to provide users with small generators of electricity [3]. These small units include fuel cells, small gas turbine or gas turbine and fuel cell hybrid device.

DG plays the role of load shifting and load balancing. It can compensate for the lack of security and stability of large power grids, avoid large-scale power outage, and provide users with more secure and stable supply of electricity [3].

68.3 Mathematical Model of Distributed Power Distribution Planning

In the distribution network planning, according the decision variables can be divided into two types, one is the single planning and another is coordinated planning [2]. Single planning is to optimize the installation location and capacity of distributed generation equipment in the condition of the feeder lines and substation configuration does not change; the coordinated planning is for global optimization planning, and includes the feeder lines. This paper focuses on the former.

68.3.1 Multi-Goal Programming Objective Function

In this paper, we focus on the distributed power distribution planning problem, mainly to consider economy and security. Ultimately, we establish the multi-objective model for the objectives of the network minimum network loss, minimum average deviation of the node voltage and the minimum total investment cost [4]. The objective function of the total investment cost φ is as follows:

$$\min\varphi = \sum\nolimits_{i=1}^{n_{DG}} (C_{i1} + C_{i2})\, P_{DGi} \tag{68.1}$$

In the formula, n_{DG} is the number of distributed generation equipment installed; P_{DGi} is the DG rated capacity installed in the node i; C_1, C_2 were distributed device unit capacity of node i overall equipment costs and installation costs.

The objective function of the network minimum loss is as follows:

$$\min P_{loss} = \sum\nolimits_{i=1}^{N} R_i(P_i^2 + Q_i^2)/\,|U_i|^2 \tag{68.2}$$

P_{loss} is the loss of active network; N is the number of slip; R_i is the slip resistance; P_i, Q_i, U_i, respectively, for node i active power, reactive power and voltage.

The objective function of the average deviation is as follows, U_i* is the rated voltage of the node i:

$$\min U_{ad} = \frac{1}{N}\sum\nolimits_{i=1}^{N} \left|U_i - U_i^*\right| \tag{68.3}$$

68.3.2 Constraint Conditions

The Equality constraints are the distributed generation access with the grid system power balance equation:

$$\begin{cases} P_{Gi} + P_{Di} - P_{Li} = U_i \sum\nolimits_{j=1}^{N} U_j(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}) \\ Q_{Gi} + Q_{Di} - Q_{Li} = U_i \sum\nolimits_{j=1}^{N} U_j(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) \end{cases} \tag{68.4}$$

$$\begin{cases} |U_i|^{\min} \le |U_i| \le |U_i|^{\max} \\ |I_i| \le |I_i|^{\max} \\ P_{DGi}^{\min} \le P_{DGi} \le P_{DGi}^{\max} \\ \sum\nolimits_{i=1}^{n_{DG}} P_{DGi} \le \alpha \sum\nolimits_{i=1}^{N} P_{LDi} \end{cases} \tag{68.5}$$

In this formula, P_{Gi}, Q_{Gi} is the injected generator active power and reactive power of i; P_{Di}, Q_{Di} is injected distributed generation; P_{Li}, Q_{Li} is the active power and reactive power; U_i and U_j are the voltage of the first node i and the end node j.

The inequality constraints include: the node voltage upper and lower limits, and the distributed power generation capacity, the maximum limit of the slip power.

68.3.3 Transform the Multiple Objectives into Single Objective

For the reunification of the dimension of each sub-goal, we introduced the general linear piecewise function to represent the fuzzy membership function for each sub-goal [5].

$$\mu_i = \begin{cases} 1, (f_i \leq f_i^*) \\ \dfrac{f_i^- - f_i}{f_i^- - f_i^*}, (f_i^* \leq f_i \leq f_i^-) \\ 0, (f_i \geq f_i^-) \end{cases} \tag{68.6}$$

$$\max\lambda = \min\{\mu_1, \mu_2, \mu_3\} \tag{68.7}$$

In this formula, μ_i is the corresponding sub-goals of the membership; f_i^- is the maximum function value of the corresponding sub-goals; f_i^*, optimized to get the best target for the corresponding sub-goals; n is the value of overall satisfaction.

68.4 Hybrid Immune Algorithm

Artificial immune algorithm is mainly used in the operation mechanism of the artificial immune system to solve practical problems. The clonal selection algorithm in this paper is also based on immune algorithm.

68.4.1 Clonal Selection Algorithm

Clonal selection algorithm simulates the mechanism of biological immune system [6] (Fig. 68.1). Generally we put the objective function to be optimized and constraints as the antigen and the algorithm steps are as follows:

Step 1 Initialization: randomly generated N-antibody corresponds to a possible solution.
Step 2 Classification: N antibody decomposition of m and r antibody composed of two in part A_m, A_r, respectively, into the memory set of antibodies and the rest, the antibodies who can enter the memory set have a higher affinity.
Step 3 Cloning: select the k-affinity antibodies were cloned; the number of clones is proportional to their affinity.
Step 4 Mutation: mutation operation on the cloned antibodies and the mutation rate is inversely proportional to affinity.
Step 5 Reselect: recalculate the affinity of the mutated antibodies to formulate the new memory set.

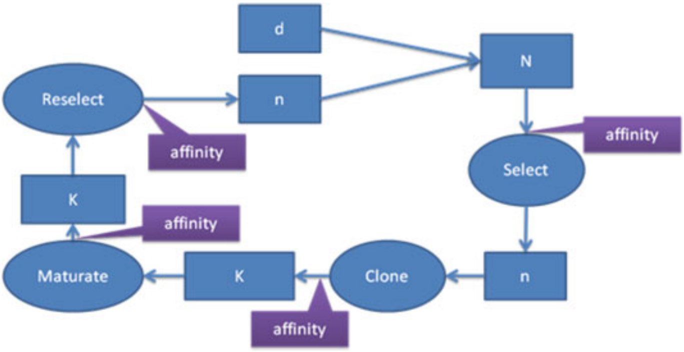

Fig. 68.1 Standard clonal selection algorithm processes

Step 6 Demise: simulated biological clonal selection process 5 % of B cells die a natural death.
Step 7 Check whether it meets the termination condition, if terminate, otherwise go to step 2 into the next iteration.

68.4.2 Improved Clonal Selection Algorithm

The study found that the algorithm has several obvious shortcomings:

1. High-frequency variation rate lack the automatic adjustment feature.
2. The lack of memory bank.
3. Lack of collaboration and communication between the antibodies.

68.4.2.1 Particle Swarm Optimization (PSO)

Compared with the artificial immune algorithm, particle swarm optimization algorithm has a lot to learn from its advantages. The standard particle swarm optimization algorithm solves the optimization problems through the cooperation and competition between particle swarm individual [7]. Each individual in the population referred to as particles, each particle represents the problem to be optimized a possible solution.

Update position and velocity with the following formula:

$$\begin{cases} v_1(t+1) = \omega v_1(t) + c_1 R_1(p_1(t) - x_1(t)) + c_2 R_2(p_g(t) - x_1(t)) \\ x_1(t+1) = x_1(t) + v_1(t+1) \end{cases} \tag{68.8}$$

In this formula, ω is the Inertia coefficient, c_1 and c_2 are the acceleration constant; $R_1 \sim U(0, 1)$ and $R_2 \sim U(0, 1)$ are two independent random functions.

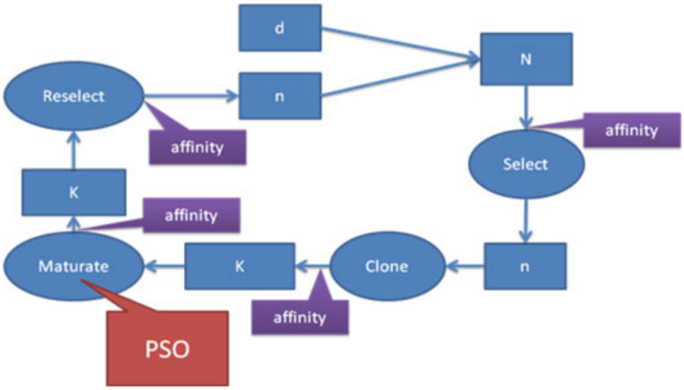

Fig. 68.2 Improved clonal selection algorithm processes

68.4.2.2 Hybrid Immune Algorithm

In this paper, we use the particle swarm optimization to compensate for clonal selection algorithm's shortcomings, such as the long training time, and to reduce the population size; at the same time, we use the clonal selection algorithm's diversity to compensate for the shortcomings of PSO to improve search accuracy.

Through the clonal selection, each antibody has used its own historical information, therefore when introduce the evolution equation of particle swarm optimization algorithm, we should only consider approaching the global optimum, then we use PSO formula which is mentioned above, so that evolution has a more clear direction to improve the convergence rate, while taking advantage of the variation in the immune algorithm and demise the operation to ensure that the diversity of antibodies, both the use of the cloning algorithm to maintain the advantages of antibody diversity, but also advantage of the characteristics of group information sharing in the PSO algorithm (Fig. 68.2).

Consider each antibody as a particle in the particle swarm optimization, at the beginning of the clonal selection algorithm, determine the affinity vector F of random initial population of A_N, then order to do the steps of the clonal selection algorithm, and then update the velocity and position of existing antibody using the PSO algorithm, the limit does not exceed the boundary, and update P_g, the guidance of antibodies to high frequency variation, followed by clonal selection algorithm receptor editing process.

68.4.3 *Hybrid Immune Algorithm to Solve the Problem of Distribution*

In this paper, in order to solve the planning problem of distributed power distribution in the distribution network, simplifying the problem to determine the distributed

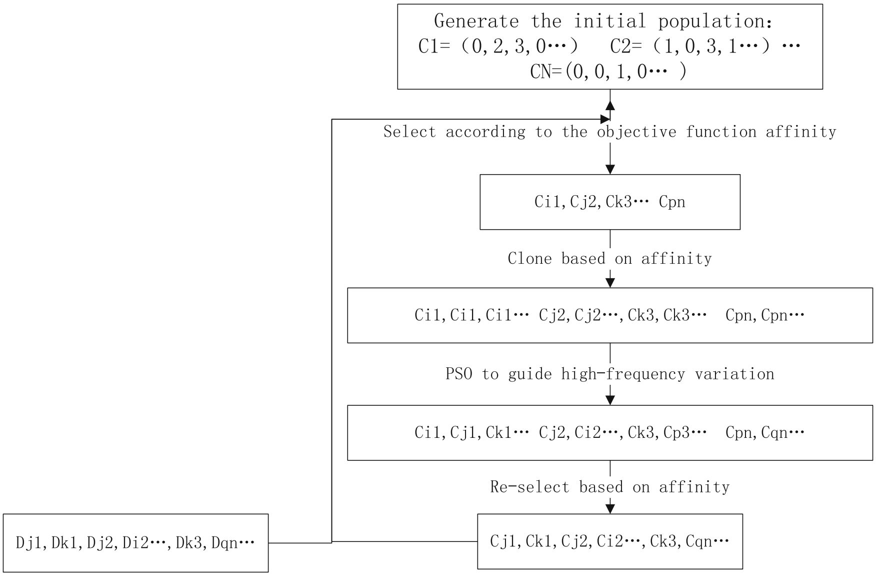

Fig. 68.3 Hybrid immune algorithm processes

power distribution network in the location and capacity. We use real number encoding method to express the location and capacity of distributed power variables, and assume that the distributed power installed in the load node, and one can only install one distributed power. The radial distribution network allows N nodes to install, distributed power building programs use a set of variables $C = \{c_1, c_2 \ldots c_n\}$ to represent [1]. The magnitude of c_i, illustrates the construction of distributed power corresponding to the load node i, if $c_i = 0$ indicates the load of node i is not the construction of distributed power; if $c_i = 2$ indicates 20 kVA, and so on.

Using HIA to find the optimal solution, we first need to solve the problem how to initial antibody population. Generally is generated randomly, but the number of such infeasible solutions would be too large, in turn affect the search vegetarian range and convergence speed. Therefore when we generate the initial antibody population must be restrained by some constraints. The first one is the total capacity of the distributed power can not exceed the maximum capacity of planned distribution network to new load, and verify the capacity of each power must be within the rated range. All of the N antibodies should be generated in this way.

In the solution process, the HIA starting from the initial antibody population based on the affinity function, and then selection, cloning, mutation; PSO algorithm is used to achieve the exchange of information between individuals and guidie high frequency variation. The specific process is as follows [5] (Fig. 68.3).

Table 68.1 IEEE 33 node test system

Method	DG access location	DG installation number	Active power loss before the DG (kW)	Active power loss after the DG (kW)
HIA	30	2	180.918	82.1835
PSO	30	2	180.778	82.1820

68.5 Numerical Example

We use the IEEE 33 node distribution test system to verify the algorithm. It is a pure radial distribution network; has 33 nodes, 32 branches.

The total active and reactive powers of the load were 298 MW and 129 Mvar. HIA parameter is set to: the number of antibody M = 60, the maximum number of iterations to 100, and an accuracy of d = 0.0001. Calculated using HIA in the previous section, the first randomly generated 60 solutions within the constraints, to calculate the antigen–antibody affinity according to the objective function (68.7), and iteratively until the termination condition. By the above calculation, the simulation results are as follows: the location of 30 is the best access location of the distributed power, at this time the system active power loss for 82.1820 kW optimized active power loss decreased rate of 54.53 %. In order to verify the effectiveness and superiority of the HIA, the algorithm with the standard PSO calculations were compared the results in the table.

It can be seen from Table 68.1 that the calculated results are basically the same in HIA and PSO, it proves that a HIA for distributed power supply location and constant volume is feasible and effective. The DG's access makes the active power loss is much lower, it is indicate that the DG's access could greatly reduce the active power loss if the location and constant volume is planned reasonably. Shown in Fig. 68.4 for the convergence of two algorithms in the optimization process, in this paper, the HIA have a certain improvement in convergence and adaptability than the standard PSO.

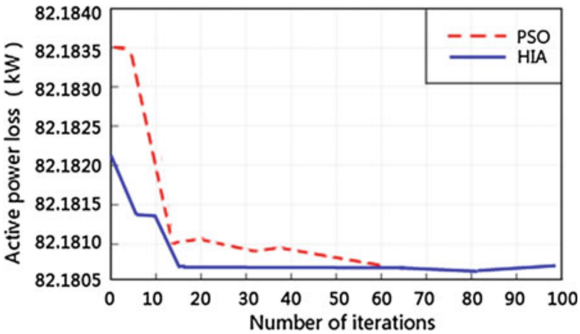

Fig. 68.4 HIA and PSO convergence curve

68.6 Conclusion

In the rapid development of smart grid, distributed power generation equipment has begun large-scale applications; an access to a variety of distributed power securely and reliably has important significance [3]. This article is just start on this point; it adopts the multi-objective optimization model of distribution network planning, and uses HIA in distribution planning. HIA mainly uses the clonal selection theory as the mechanism, and considers the PSO algorithm as the guidance for high-frequency variation, which can adjust the direction of the variability during the optimization process; this can improve the computational efficiency of the algorithm and avoid falling into local optimum too early. In order to verify the algorithm, we used the IEEE 33 node test system for simulation and put the results to compare with the standard PSO algorithm; proved its effectiveness and efficiency.

As a preliminary study, this paper only consider distributed power distribution planning problem in a pure environment, although we used multi-objective optimization methods, there still have many influencing factors did not taken into account, and need for the further research.

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