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Fault diagnosis of smart grid based on improved immune optimization algorithm[1]

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Abstract. Aiming at the problem of fault diagnosis of smart grid, an improved immune optimization algorithm was proposed in this paper. Firstly, the idea of chaos algorithm was integrated into the immune optimization algorithm to make the algorithm have stronger global optimization ability; secondly, an improved mutation operator was proposed to make the algorithm be in the vicinity of the current optimal solution for local search, so as to strengthen the local search capabilities. Simulation results show that the performance of the improved immune optimization algorithm is superior to that of the traditional immune optimization algorithm, and it has better stability and search ability, and is more suitable for applications requiring high stability and accuracy.

Key words. Smart grid, fault diagnosis, immune optimization, chaos algorithm.

1. Introduction

With the increase in the type of electricity, the levels of distribution network voltage continue to increase, and the structure of distribution network is also more complex. Electrical wiring aging, man-made operational errors or natural disasters and other reasons have caused the occurrence of the distribution network. Therefore, how to improve the speed of fault diagnosis and the efficiency of distribution network has become a hot research topic.

In order to meet the goal of actual fault diagnosis and realize the goal of fault location and fast location in the distribution network, many experts and scholars

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who engage in the electric power research and fault location research at home and abroad have put forward many methods. In reference [1], the binary group intelligent algorithm was used to optimize the fault diagnosis of the smart grid. In reference [2], the binary particle swarm optimization algorithm was used to optimize the fault diagnosis of the smart grid. In reference [3], an improved genetic algorithm was used to optimize BP-NN to optimize the fault diagnosis of smart grid.

The immune optimization algorithm is an intelligent optimization algorithm developed in recent years [4, 5], which draws on the immune system to deal with the performance of the pathogen. As with the genetic algorithm, the immune optimization algorithm has been optimized according to the law that "it is not the strongest of the species that survive, but the one most responsive to change" in body system. Immune evolutionary algorithm, as an intelligent algorithm with global optimization ability, generates the offspring population based on the optimal solution of the previous generation, and then uses the convergence of the best individual instead of the population's convergence, which has good adaptability and distribution. Therefore, immune evolutionary algorithm has been applied in many optimization problems because of the excellent effect. But the algorithm is easy to fall into the local optimum, and the convergence is slow.

In this paper, an improved immune algorithm was proposed to solve the problem of intelligent fault diagnosis. A new mutation operator was proposed, which not only has the ability of global optimization, but also improves the convergence speed. The simulation results show that the improved algorithm is effective.

2. Methodology

The idea of establishing the optimal model for fault diagnosis of smart grid is to establish a model to minimize the optimization goal based on the logical relationship between the faulty elements and the protection and switching action. Then the fault diagnosis problem is transformed into the 0–1 programming problem, so that the corresponding optimization algorithm can be optimized to obtain an optimal failure hypothesis.

2.1. Factors affecting the smart grid fault diagnosis

The factors that affect the fault diagnosis of the smart grid can be summarized into four categories: protection and error actions in circuit breaker, error reporting in information transmission, incomplete model building, uncertainties in time and space dimensions.

When there is a problem in the related equipment in smart grid, the device with the protection device can quickly make the action, in order to jump the corresponding circuit breaker, so that the problem of equipment will be isolated, and other normal equipment can continue to work without affected. However, when the protection or circuit breaker malfunction causes errors in other normal equipment operation, it will lead to power failure in grid area that should not have been affected, thus making things more serious.

During the process of transmission of information in smart grid system, the important information transmission distortion in the smart grid system is caused by the errors of the relevant equipment in the sampling process, the unexplained interruption of the channel or other reasons, which will cause the problem of failure to report information in a timely manner, or to report a delay, thus leading to false positives and making troubleshooting more difficult.

In recent years, there has been lots of research on smart grid fault diagnosis, and research on diagnostic model has also made great progress. Most of the major models consider the error reporting in the smart grid equipment, protection and circuit breaker action and transmission of information, but these factors are not perfect with several problems: the possibility of expansion faults caused by power grid equipment are not considered. The consistency of protection action is not taken into account in the measurement function. Sampling data is mainly taken from fault diagnosis, which lacks the overall consideration.

When the fault occurred in the normal work of the smart grid, there is no way to know in advance that how long the failure occurred and how many times it occurred during malfunction. The fault problem may be found in 10 seconds if problem is quite simple. Once the fault problem becomes serious, the time will be extended to a few minutes, and different time period will result in difference in the number of fault events. So the time and space dimensions in the fault diagnosis of the smart grid have uncertainties.

Based on the idea of reference [6], the fault diagnosis problem of the smart grid is expressed as the minimization of the objective function shown in the equation

$$E(S) = \sum_{k=1}^{n_r} |r_k - r_k^*(S)| + \sum_{j=1}^{n_c} \left| c_j - c_j^*(S,R) \right| , \tag{1}$$

where S is an n-dimensional vector representing the state of the elements in the system (n is the number of elements in the system). Equality $S_i = 0$ represents that the ith element is normal; $S_i = 1$ means that the ith element is faulted. Symbol n_r denotes the total number of protection, n_c is the total number of circuit breakers, r_k is the kth element in R representing the real state of the kth protection (non-action state or action state), in which R is the n_r-dimensional vector representing the actual state of the n_r protection. Quantity $r_k^*(S)$ is the kth element in $R^*(S)$ representing the desired state of the kth protection; if the kth one protects this action, then $r_k^*(S) = 1$, or $r_k^*(S) = 0$; $R^*(S)$ is the n_r-dimensional vector representing the expected state of the n_rth protection. The value of $R^*(S)$ was decided by the state of S; c_j is the jth element in C representing the real state of the jth circuit breaker. Equality $c_j = 0$ means that the jth circuit breaker is in the un-tripped state, $c_j = 1$ means that the jth circuit breaker is in the tripped state. Symbol C denotes the n_c-dimensional vector representing the actual state of the n_cth circuit breaker and $c_j^*(S,R)$ is the jth element in $C^*(S,R)$ representing the expected state of the jth circuit breaker. If the jth circuit breaker ought to trip, then $c_j^*(S,R) = 1$, or $c_j^*(S,R) = 0$. Symbol $C^*(S,R)$ denotes the n_c-dimensional vector representing the expected state of the n_cth circuit breaker. The value of $C^*(S,R)$ was decided by the states of S and R.

Based on the above model, it can be found that the model exhibits some flaws, leaves out of consideration on switch and wrong action in the circuit breaker, such as malfunction and refusal. Therefore, new factors can be added into the modeling on the basis of the above model [7]. The model is as follows:

$$E(G) = \sum_{i=1}^{Z} \left\| r_i = r_i^{'} \right\| + \sum_{i=1}^{K} \left\| c_i = c_i^{'} \right\| +$$

$$+ w_1 \sum_{i=1}^{Z+K} \|d_{\mathrm{i}}\| + w_2 \sum_{i=1}^{Z+K} \|m_{\mathrm{i}}\| + w_3 \sum_{i=1}^{2Z+2K} \|F_i(S, R, C, M, D)\| \tag{2}$$

In the above model expression, $\|\cdot\|$ represents the norm of the logical variable; on the right side of the above equation, the first two items are the false action logic of the protection and circuit breaker representing the error report of the warning message. On the right side, the third and fourth items represent abnormal action of protection of a circuit breaker, and the last one represents the constraints of the model; w_1, w_2, and w_3 are the model weights. Particularly, w_1 and w_2 represent the weights of abnormal action of protection and circuit breaker, while w_3 is the model of the protection factor.

The weight value of the model has great influence on the practicability of the model. The correct weights represent the model more practical, therefore, the weight of the model should be chosen. Weight w_3 as the guaranteed coefficient of the model has greater value than 1, and w_1 and w_2 represent the weights of abnormal action of protection and circuit breaker. We set the sum of w_1 and w_2 to 1, and their further identification is carried out by the AHP method.

Analytic Hierarchy Process divides the factors related to decision-making into target layer, scheme layer and criterion layer. The decision-making mode is quantitative and qualitative analysis for relevant factors, which was proposed by Suttie, a famous American operational research expert, in the early 1970s of 20th century.

Analytic Hierarchy Process refers to regard a complex decision-making problem with multiple decision objects as a multi-layer system. It divides the goals of decision into multiple targets or criteria, and then divides them into several levels with certain indexes and constraints. The qualitative index fuzzy quantification method is used to calculate the single rank and the total ranking of the hierarchy, which can be used as the multi-objective and multi-scheme system method to optimize the decision [8]. Since it can be turned into simple-weight polynomials, this method has been applied to many practical optimization problems [9].

The steps for the determination of weight are:

(1) The first step is to establish hierarchical structure, the top layer is abnormal action of the protection and circuit breaker. The bottom layer is the object layer, namely, the rejecting action of protection and circuit breaker, and malfunction of protection and circuit breaker.

(2) The second step is to construct a 6-person decision-making group, the individual can judge two factors according to the relative importance of the scale method,

so as to obtain pairwise comparison matrix according to the judgment results.

(3) The third step is to calculate the maximum eigenvalue of each comparison matrix and its corresponding eigenvector.

(4) The fourth step is to use consistency indicators for testing, if they pass the test, the normalization of the feature vector can be obtained after the weight vector.

(5) The final weight of each factor is the average of the six groups of weight vector.

Finally, the analytic hierarchy process can be drawn: $w_1 = 0.64$, $w_2 = 0.36$.

2.2. Improvement of the algorithm

The artificial immune optimization algorithm is an optimization algorithm for simulating the immune system of the human body and a new intelligent optimization algorithm based on the immune system. The immune algorithm is characterized by the diversity of the population and the maintenance mechanism of the algorithm. Compared with other algorithms, it avoids to dealing with more difficult precocious problem. And it performs well in global optimization. The occurrence time of algorithm is later than some of the classic intelligent algorithm. The theory has developed just over a decade. Farmer and other scholars in the 1980s proposed basic framework of the immune system based on the immune system theory to explore the connection between immune system and other artificial intelligence methods, thus creating the immune system.

General steps of immune algorithm is as follows:

(1) Analyze problems that needed to be resolved. Figure out the solution of the mathematical model.

(2) Generate the first generation population. Randomly generate Nth individuals, and then compose the first generation solution population with the use of m individuals taken from Memory Bank, where m is the number of individuals inside the memory.

(3) Evaluate the above individuals within the population. The evaluation of the individual in the immune optimization algorithm is based on the expected reproduction rate P of the individual.

(4) Generate the parent population. The initial population is sorted in descending order by the expected reproduction rate P, and then the previous individual is extracted to form the parent population; and the previous individual is placed in the memory bank.

(5) If the maximum number of iterations is reached, the algorithm terminates; if the maximum number of iterations is not reached, the algorithm continues to be optimized.

(6) Generate new populations. According to the optimization result obtained in the step (4), the antibody is crossed, selected and mutated to generate new population, and then the individuals in the memory are taken out to form new population.

(7) Go back to perform step (3).

Some definitions of immune algorithm include:

The affinity between the antibody and the antigen in the algorithm is used to indicate the recognition degree of the antigen by the antibody, the affinity function is $A_V = \frac{1}{F_V}$, where F_V is the objective function, namely, the optimization model:

$$E(G) = \sum_{i=1}^{Z} \left\| r_i = r_i^{'} \right\| + \sum_{i=1}^{K} \left\| c_i = c_i^{'} \right\| +$$

$$+ w_1 \sum_{i=1}^{Z+K} \|d_{\mathrm{i}}\| + w_2 \sum_{i=1}^{Z+K} \|m_{\mathrm{i}}\| + w_3 \sum_{i=1}^{2Z+2K} \|F_i(S,R,C,M,D)\| \ .$$

The affinity between the two antibodies represents the degree of similarity between the two antibodies, and the immune optimization algorithm expresses the affinity by the equation

$$S_{v,s} = \frac{k_{v,s}}{L} \ , \tag{3}$$

where $k_{v,s}$ is the same number of bits between antibody v and antibody s; L is the length of the antibody. Finally,

$$C_V = \frac{1}{N} \sum_{j \in N} S_{v,s} \ , \tag{4}$$

where N is the total number of antibodies. Quantity $S_{v,s}$ is given as

$$S_{v,s} = \begin{cases} 1 & S_{v,s} > T \ , \\ 0 & \text{others} \ \ , \end{cases}$$

where T is a preset threshold value.

In a population, the expected reproductive probability of an individual is determined on the basis of both the antibody-antigen affinity A_V and the antibody concentration C_V namely:

$$P = \alpha \frac{A_V}{\sum A_V} + (1-\alpha) \frac{C_V}{\sum C_V} \tag{5}$$

where α is constant. According to the above formula, it can be seen that the greater the adaptability value of the corresponding adaptability, the greater the expected reproductive probability. The larger the value of the individual corresponding concentration, the smaller the expected reproductive probability. It not only strengthens the individual with high adaptability, but also weakens the individual with high concentration, and then maintains the individual diversity.

Because the clonal selection in immune algorithm is mainly judge on the basis of the size of the affinity. Only the larger affinity and stronger combining capacity of antibody can be maintained to the next step optimization. Mutation operation is relatively antibody with strong binding capacity. Therefore, the algorithm is easy to fall into the local optimal solution, and the convergence speed is slow, so the immune algorithm is needed to be improved accordingly.

2.3. Introduction of chaos algorithm

The chaos algorithm has the characteristics of randomness and ergodicity, so it can be searched completely within the set range, so it can jump out of the local optimal solution. So many optimization algorithms and chaos algorithm are combined to optimize the effect.The chaos model used in this paper is Logistic mapping model and its equation is:

$$x_{k+1} = \lambda x_k(1 - x_k) \qquad x_k \in [0,\ 1]\ . \tag{6}$$

In the above formula, λ is the control parameters, and its value is between 0 and 4. Logistic map is an irreversible range between 0 and 1. When $\lambda = 4$, the system enters the so-called chaotic state. The initial point is set in any position, and can generate points between 0 and 1. A logistic map is used to obtain a chaotic point sequence, which is then transformed into a variable of the solution space of the problem to be solved, and the optimal solution for problem can be searched.

In this paper, the chaotic algorithm is used to optimize the current optimal solution, and the current optimal solution is mapped into the chaotic variable [0,1]. According to $x_i^{'} = c_i + d_i\beta_i^{(\mu+1)}$, r chaotic variables are selected into the optimal variables of the rth equation (4) to transfer the optimal variables into chaotic variables $x_i^{'}$, which is the variation range of the chaotic variable corresponding to the range of the optimal variable. Here, $c_i d_i$ are the changed constant, $i = 1, 2, \cdots r$. Let

$$X = (x_1 x_2 \cdots x_r), \quad X^{'} = (x_1^{'} x_2^{'} \cdots x_r^{'})\,, \tag{7}$$

and then, chaotic variables are encoded.

2.4. Improved mutation operator

In some traditional optimization algorithms, the mutation operator can realize the searching in the whole solution space by the random position transformation. The search ability of the algorithm is greatly enhanced, but the convergence speed is slow due to the lack of regular search. The mutation operator which is the same as the traditional mutation operator is proposed when the normal algorithm is optimized. However, if necessary, the mutation operator can also search the near optimal solution to strengthen a certain local search capabilities.

Definition: let N-dimensional optimal problem feasible region $[l_i, u_i]$, $i = 0, 1, \cdots, N$, Suppose the parent is $a_1 = [a_{11} a_{12} \cdots a_{1N}]$. After mutation of the offspring, improved mutation algorithms are obtained $T_{mm}(a_1) = \left[a_{11}^{'} a_{12}^{'} \cdots a_{1N}^{'}\right]$, which makes it possible for different mutation operators to act on individual components according to different probabilities or remain unchanged:

$$a'_{1i} = \begin{cases} a_{1,i} + N(0,1), rand < p_i, \\ a_{1,i}, p_i \leq rand \leq p_j, \\ l(i) + rand \times u(i) - l(i)), rand \geq p_j, \end{cases} \tag{8}$$

where $i = 1, 2, \cdots, N, N(0,1)$ is a random number obeying the standard normal distribution; rand is a random number between [0,1] with uniform distribution.

In the equation, $a_{1,i}$ in the antibody a_1 is the probability ofp_i in Gaussian variation. That is, variation around the individual can enhance the local search ability of the algorithm and improve the local search precision of the algorithm; the probability of $1-p_j$ was used for the variation in global scope, which can maintain the diversity of the population, improve the global search ability of the algorithm, and make the whole group easily jump out of the local optimal.

3. Experiment simulation

In order to verify the effectiveness of this algorithm, taking the actual distribution network system as an example. A simple scheme of the grid system is shown in Fig. 1. In Fig. 1, $S_1 - S_8$are eight elements, $c_1 - c_7$ are circuit breakers. Finally, $r_1 - r_{20}$ are 20 protection devices.

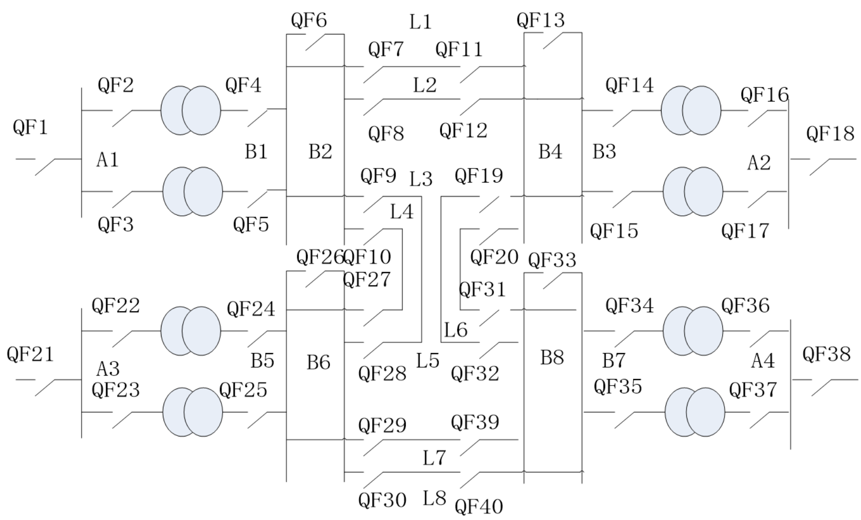

Fig. 1. Actual distribution of network system

Taking the action information of 7 grid protections and circuit breakers as examples, algorithm in this paper is used to optimize

a. protect B_{im}, L_{2Rs}, L_{4Rs} action, switches $QF_4, QF_5, QF_7, QF_9, QF_{12}, QF_{27}$ were tripped;

b. protect B_{1m}, L_{1Sp}, L_{1Rm} action, switches $QF_4, QF_5, QF_6, QF_7, QF_9, QF_{11}$ were

tripped;
c. protect $B_{1m}, B_{2m}, L_{1Sm}, L_{1Rp}, L_{2Sp}, L_{2Rm}$, action, switches $QF_4, QF_5, QF_6, QF_7, QF_8, QF_9, QF_{10}, QF_{11}, QF_{12}$ were tripped;
d. protect T_{3p}, L_{7Sp}, L_{2Rp} action, switches $QF_{14}, QF_{16}, QF_{29}, QF_{39}$ were tripped;
e. protect T_{5s}, T_{6s} action, switches $QF_{22}, QF_{23}, QF_{24}, QF_{25}$ were tripped;
f. protect $T_{7m}, T_{8p}, B_{7pm}, B_{8m}, L_{5Sm}, L_{5Rp}, L_{6Ss}, L_{7Sp}, L_{7Rm}, L_{8Ss}$ action, switches $QF_{19}, QF_{20}, QF_{29}, QF_{30}, QF_{32}, QF_{33}, QF_{34}, QF_{35}, QF_{36}, QF_{37}, QF_{39}$ were tripped;
g. protect $L_{1Sm}, L_{1Rp}, L_{2Sp}, L_{2Rp}, L_{7Sp}, L_{7Rm}, L_{8Sp}, L_{8Rm}$ action, switches $QF_7, QF_8, QF_{11}, QF_{12}, QF_{29}, QF_{30}, QF_{39}, QF_{40}$ were tripped.

As can be seen from Table 1, the optimization results in this paper are the same as those in reference [9], which proves that the proposed algorithm can effectively solve the fault diagnosis problem of the smart grid, which can be found in the convergence algebra. This algorithm can converge to the global optimal solution more quickly when solving the same problem.

Table 1. Optimized results

Sequence of grid action information	Optimized results of reference [11]	Mean convergence generations	Optimized results of algorithm in this paper	Mean convergence generations
a	B_1	23	B_1	36
b	B_1L_1	53	B_1L_1	145
c	$B_1B_2L_1L_2$	69	$B_1B_2L_1L_2$	98
d	T_3T_7	53	T_3T_7	79
e	A_3	59	A_3	82
f	$L_5L_7B_7B_8T_7T_8$	97	$L_5L_7B_7B_8T_7T_8$	148
g	$L_1L_2L_7L_8$	87	$L_1L_2L_7L_8$	135

In order to directly prove the performance of the improved algorithm, b was taken as an example to simulate the experiment. Figure 2 shows the simulation results. The results of the optimal adaptability value and the average adaptability value were compared. And the average adaptability value is higher. In the later period, the algorithm can converge to the optimal solution nearby.

In order to further verify the optimization performance of the algorithm, the algorithm in this paper was compared with the immune optimization algorithm, b. and c. were taken as examples to optimize, and then the performance of the proposed algorithm and the traditional immune algorithm in the different specifications of the smart grid fault optimization was compared. The results are shown in Figs. 3 and 4.

From the simulation in Fig. 2, it can be found that, compared with the traditional immune algorithm, the integration of the chaotic algorithm has the following advantages:

(1) It can strengthen the global search ability of the algorithm.

(2) It can improve the mutation operator, which can make the mutation operation

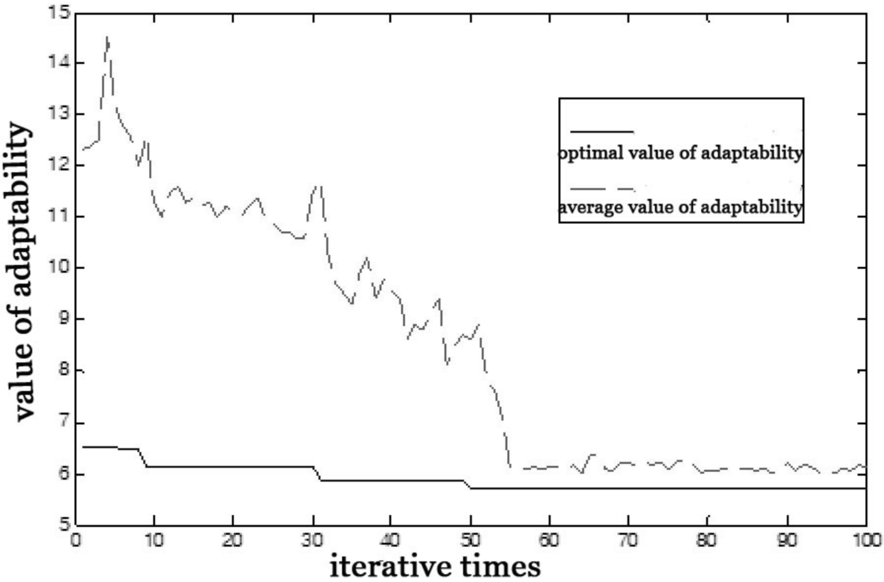

Fig. 2. Convergence curve of the algorithm

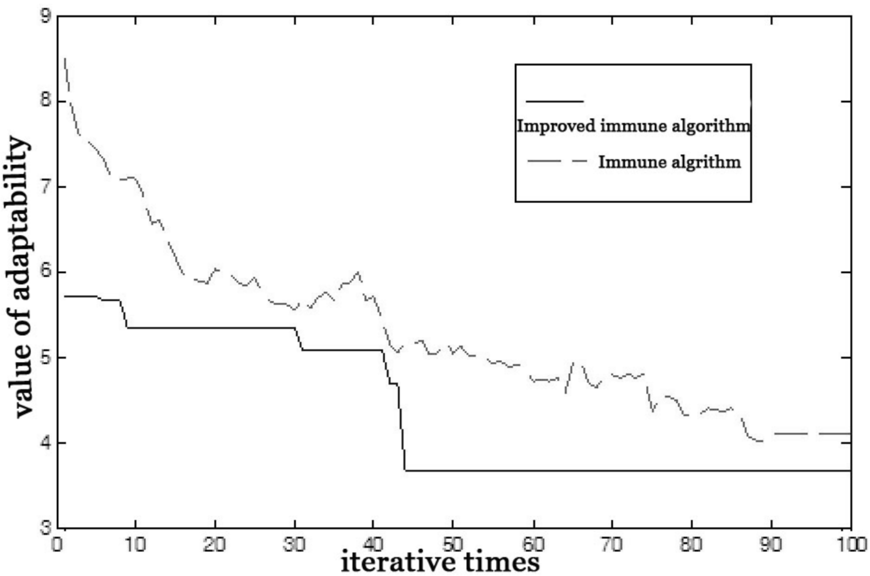

Fig. 3. Convergence of algorithm (example b.)

in the vicinity of the current optimal solution speed up the convergence rate, thus improving immune algorithm in the optimization efficiency.

Compared with the traditional immune algorithm, the integration of the chaotic

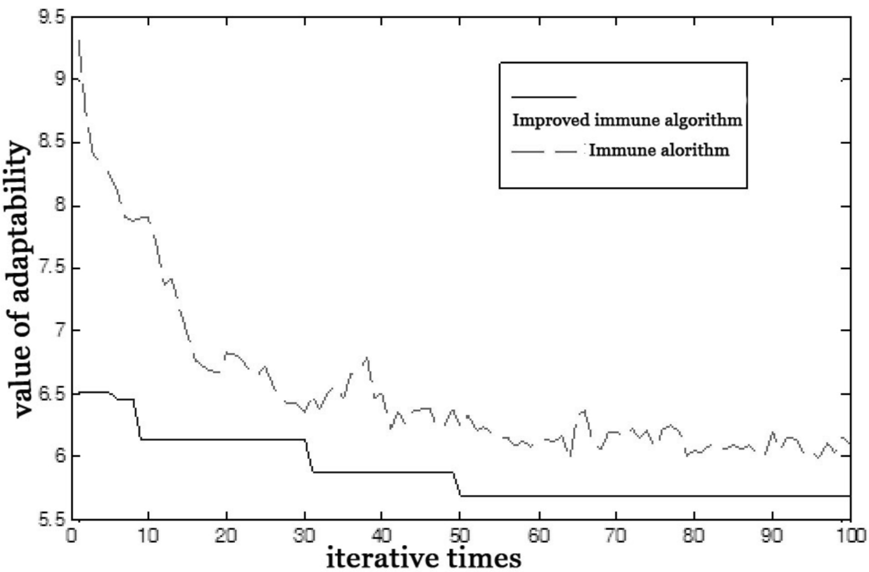

Fig. 4. Convergence of algorithm (example c.)

algorithm can exhibit a good performance, which can ensure a faster convergence to the optimal solution, so as to find a better solution.

4. Conclusion

In this paper, an improved immune algorithm was proposed to solve the problem of smart grid fault diagnosis, and the idea of chaos algorithm was put forward. The current optimal solution of the iteration of the algorithm will not fall into local optimization and enhance the global optimization ability of the algorithm, and a new mutation operator can make the mutation operation in the vicinity of the current optimal solution, so that the improved algorithm not only has the ability of global optimization, but also improves the convergence speed. Finally, in this study, the optimization of the power network diagnosis problem was compared with the traditional immune algorithm, and the effectiveness of the algorithm was proved.

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