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Fault diagnosis of Electric Power Grid Based on Improved RBF Neural Network

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Abstract

This paper introduces a novel clustering algorithm that combines crisp and fuzzy clustering. It not only has the high accuracy of fuzzy clustering, but also reduces the dependency on initialization. Specifically, it constitutes a fast learning process and therefore, the convergence rate and the accuracy of the RBFNN are greatly improved. The simulation results show that this strategy is successfully applied to the fault diagnosis of electric power grid. The training speed and the fault-tolerance of information aberrance, which comes from the maloperation of the protections and breakers, are superior to the traditional RBFNN.

Keywords: *fault diagnosis, RBF neural network, crisp clustering, fuzzy clustering, electric power grid*

1. Introduction

With a substantial increase of the types and quantities of the grid electrical equipments, the increasing complexity of operating conditions coupled with natural disasters and misuse make the grid fault occurs frequently. If the partial fault of the power grid can not received timely treatment, it will lead to a large-scale blackout, which seriously endangers the stable operation of the power system. However, in the case of the abnormal operation, multi-fault of protective relays and circuit breakers, fast and accurate fault diagnosis is very difficult to achieve for the influx of massive amounts of information [1-3]. In recent years, with the development of computer technology and intelligent theory, a variety of artificial intelligent and optimization methods are used in power system fault diagnosis, such as fuzzy theory, optimization techniques, expert systems, Petri networks, data mining [7, 8]. Artificial Neural Networks with its self-learning ability, fault tolerance, and parallel information processing capabilities, is more and more used in the study of power system fault diagnosis, especially the RBFNN that shows its advantages in practical engineering applications [8]. RBFNN has a any function approximation ability in theory, training and execution time is less than other commonly used network learning algorithms, and the network has a certain degree of fault tolerance for the non- training detection samples.

There are a variety of learning algorithms of RBFNN during the RBFNN training period, [9-13], a clustering algorithm which fully takes into account the data inherent distribution relationship is proposed in this paper, the diagnostic result of this method is compared with the result simulated by traditional fuzzy clustering algorithm (FCM) [14, 15]. The simulation results of the 4-bus test system show that the clustering speed and the accuracy of hybrid clustering algorithm are both better than FCM algorithm.

The rest of the paper is organized as follows. In section 2, we introduce the RNFNN about its structure. In section 3, the proposed approach combined with crisp and fuzzy clustering algorithms is presented. In Section 4, it deals with the parameter estimation for the training of the RBFNN. In Section 5, the effectiveness of such a methodology is investigated by means of simulations. Finally, conclusions are drawn in Section 6.

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2. RBFNN Structure

RBFNN is a feedforward network with three-tier structure; its topology is shown in Figure 1. Input layer nodes transfer the input signals to the hidden layer, the hidden layer nodes are composed of radial action functions like Gaussian kernel function, and the output layer nodes are usually simple linear functions. When the input signal is close to the center of the base function, the hidden layer nodes will produce a larger output, which shows that this network has a capacity of local approximation. As the form of the basis function, the most commonly used is Gaussian function:

$$R^i(x) = \exp\left[-\frac{\|x - c_i\|^2}{\sigma_i^2}\right] \quad \mathrm{i} = 1,2,...,\mathrm{m} \tag{1}$$

Where x is n–dimensional input vector, c_i is the center of the i th basis function, σ_i is the width of Gaussian function, m is the number of hidden nodes. The Gaussian function above has the characteristics of simple structure, good analyticity and any order derivable.

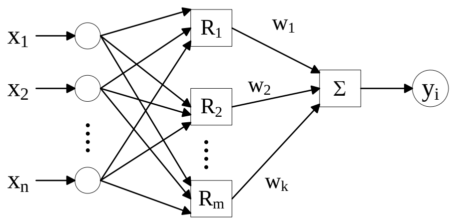

Figure 1. Structure of RBFNN

For the structure above, the input layers carry out the nonlinear mapping of $x \to R^i(x)$, while the output layers carry out the linear mapping of $R^i(x) \to y_k$, that is:

$$y_i = \sum_{i=1}^{m} w_{ik} R_i(x) \quad k = 1, 2, 3......p \tag{2}$$

Where p is the number of the output layer nodes.

3. Hybrid Fuzzy Clustering Algorithm

3.1. The Basic Theory

The core idea of the algorithm is that for those sample sets which needed to be clustered, all of the samples should be divided into three categories: one part of the samples are only belong to one of the clusters, this kind of samples is called the crisp clustering samples; another part of the samples, which are called semi - fuzzy clustering samples [16], belong to some of the clusters; the last part of the samples, which are called full fuzzy samples, belong to all cluster. From the experimental verification, this idea well considers the inherent data distribution relationship among the samples. Objective function of the clustering algorithm based on the above idea is given below. The objective function of crisp clustering [17, 18], and the objective function of fuzzy clustering are used to do a simple affine arithmetic, where the parameter θ is a variable to control the clustering speed, clustering accuracy, and dependency on initialization of the algorithm. The mathematical expression form of the objective function is shown in formula (3):

$$J_H = \theta \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik} \left\| x_k - v_i \right\|^2 + (1-\theta) \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^2 \left\| x_k - v_i \right\|^2 \tag{3}$$

Where c is the number of clusters, n is the number of samples, v_i is the random cluster centers chosen before clustering, $\theta \in [0,1)$, $u_{ik} \in [0,1]$ is the membership degree of the k-th training vector to the i-th cluster. If $\theta = 0$, the objective function will become FCM algorithm with $m = 2$; if $\theta = 1$, then it becomes crisp clustering algorithm. The constraint is shown in the following:

$$\sum_{i=1}^{c} u_{ik} = 1, \quad \forall k \tag{4}$$

According to the basic principle of the clustering algorithm, the minimum value of the objective function will be obtained under the constraint of the formula (3), if values of the degree of membership u_{ik} and the cluster center v_i are the stagnation point of Lagrange function $F(u_{ik}, \lambda_k)$ which corresponds to J_H, so the following formula can be used to solve the value:

$$F(u_{ik}, \lambda_k) = \theta \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik} \left\| x_k - v_i \right\|^2 + (1-\theta) \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^2 \left\| x_k - v_i \right\|^2 - \sum_{k=1}^{n} \lambda_k (\sum_{i=1}^{c} u_{ik} - 1) \tag{5}$$

After partial differential, we get:

$$\begin{cases} \dfrac{\partial F(u_{ik}, \lambda_k)}{\partial u_{ik}} = \theta \left\| x_k - v_i \right\|^2 + 2(1-\theta) u_{ik} \left\| x_k - v_i \right\|^2 - \lambda_k = 0 \\ \dfrac{\partial F(u_{ik}, \lambda_k)}{\partial v_i} = \theta \sum_{k=1}^{n} u_{ik} (-2)(x_k - v_i) + (1-\theta) \sum_{k=1}^{n} (u_{ik})^2 (-2)(x_k - v_i) = 0 \end{cases} \tag{6}$$

u_{ik}, v_i and λ_k can be solved by the above equation:

$$\frac{\lambda_k}{2(1-\theta)} = \frac{2 + (c-2)\theta}{2(1-\theta)} \frac{1}{\sum_{j=1}^{c} (\frac{1}{\left\| x_k - v_j \right\|})^2} \tag{7}$$

$$u_{ik} = \frac{2 + (C-2)\theta}{2(1-\theta)} \frac{1}{\sum_{v_j \in C} (\frac{\left\| x_k - v_i \right\|}{\left\| x_k - v_j \right\|})^2} - \frac{\theta}{2(1-\theta)} \tag{8}$$

$$v_i = \frac{\sum_{k=1}^{n} \left[\theta u_{ik} + (1-\theta)(u_{ik})^2 \right] x_k}{\sum_{k=1}^{n} \left[\theta u_{ik} + (1-\theta)(u_{ik})^2 \right]} \quad (1 \le i \le c) \tag{9}$$

For $u_{ik} \ge 0$, the following scaling inequality can be obtained, this equation can be used as a discriminant to judge each sample belongs to which cluster, its form is as follows:

$$\left\| x_k - v_i \right\|^2 \le \frac{2 + (c-2)\theta}{\theta} \frac{1}{\sum_{j=1}^{c} (\frac{1}{\left\| x_k - v_j \right\|})^2} \tag{10}$$

Change Equation (10) to Equation (11):

$$T_k = \left\{ v_i \in T_k : \left\| x_k - v_i \right\|^2 < \frac{2 + (\varsigma(T_k) - 2)\theta}{\theta} \times \frac{1}{\sum_{v_j \in T_k} (\frac{1}{\left\| x_k - v_i \right\|})^2} \right\} \tag{11}$$

Obviously, the Equation (11) expresses that: T_k represents the set of the cluster centers which contain the k-th sample, $\varsigma(T_k)$ represents the number of the clusters which the k-th sample is belonged to. Apparently, when $\varsigma(T_k) = 1$, $1 < \varsigma(T_k) \le c$, and $\varsigma(T_k) = 0$, the sample belongs to the crisp clustering samples, semi fuzzy clustering samples and full fuzzy samples, respectively.

3.2. The Process of Hybrid Fuzzy Algorithm

Based on the foregoing analysis, the general process of this algorithm is as follows. Firstly, classification, and next, for those samples which belong to different clusters, different methods are adopted to calculate the corresponding degree of the membership. Then, calculate cluster centers, and check the cluster center to see whether it still changes. If it changes, repeat the above steps until the change reaches a certain error threshold, then stop the algorithm, the cluster center will be got. Introduce iteration parameter v, the above algorithm is rewritten as an iterative form.

$$T_k^{(v)} = \left\{ v_i \in T_k^{(v-1)} : \left\| x_k - v_i \right\|^2 < \frac{2 + (\varsigma(T_k^{(v-1)}) - 2)\theta}{\theta} \times \frac{1}{\sum_{v_j \in T_k^{(v-1)}} (\frac{1}{\left\| x_k - v_i \right\|})^2} \right\} \tag{12}$$

Equations for calculating the degree of membership of different samples are as follows:

When $\varsigma(T_k) = 1$, the sample belongs to the crisp clustering samples. u_{ik} is calculated by Equation (13).

$$u_{ik} = \begin{cases} 1 & if \left\| x_k - v_i \right\|^2 = \min_{1 \le j \le c} \left\{ \left\| x_k - v_j \right\|^2 \right\} \\ 0 & otherwise \end{cases} \tag{13}$$

When $1 < \varsigma(T_k) \le c$, the sample belongs to the semi-fuzzy clustering samples. u_{ik} is calculated by Equation (14).

$$u_{ik} = \frac{2 + (\varsigma(T_k^{(v-1)}) - 2)\theta}{2(1-\theta)} \frac{1}{\sum_{v_j \in T_k^{(v)}} (\frac{\left\| x_k - v_i \right\|}{\left\| x_k - v_j \right\|})^2} - \frac{\theta}{2(1-\theta)} \tag{14}$$

When $\varsigma(T_k) = 0$, the sample belongs to the full fuzzy clustering samples. u_{ik} is calculated by Equation (15).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} (\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|})^2} \tag{15}$$

The degree of membership is normalized by Equation (16).

$$\hat{u}_{ik} = \frac{u_{ik}}{\sum_{j=1}^{c} u_{jk}} \qquad (1 \le i, j \le c) \tag{16}$$

The update formula of cluster center is:

$$v_i = \frac{\sum_{k=1}^{n}\left[\theta\hat{u}_{ik} + (1-\theta)(\hat{u}_{ik})^2\right]x_k}{\sum_{k=1}^{n}\left[\theta\hat{u}_{ik} + (1-\theta)(\hat{u}_{ik})^2\right]} \qquad (1 \le i \le c) \tag{17}$$

The following steps show the process of the proposed hybrid fuzzy algorithm.

Select values for c and θ. Randomly initialize $v_1, v_2, ..., v_c$, set $\text{iter} = 0$.

$$\forall k : \varsigma(T_k^{(0)}) = c\ ,\ \ T_k^{(0)} = \{v_1, v_2, ..., v_c\}$$

Step 1: Set $\text{iter} = \text{iter} + 1$.
Step 2: Use Equation (12) to update the sets $T_k^{(v)}$ and their cardinalities $\varsigma(T_k^{(v)})(1 \le k \le n)$.
Step 3: If $\varsigma(T_k^{(v)}) = 1$, use Equation (12)to calculate membership degrees $u_{ik}\,(1 \le k \le n; 1 \le i \le c)$; if $\varsigma(T_k) = 0$, use Equation (16) to calculate membership degrees; else use Equation (17).
Step 4: If $u_{ik} < 0 (1 \le k \le n; 1 \le i \le c)$, set $u_{ik} = 0$.
Step 5: Then use Equation (16) to initialize membership degrees.
Step 6: Use Equation (17) to update the cluster centers.
Step 7: If there are no noticeable changes for the cluster centers, then stop, else turn to step1.

4. Parameter Estimation of the RBFNN

In this clustering algorithm, the number of the hidden nodes equals the clusters c, while the center of the radial basis function is the clustering center $v_1, v_2, ..., v_c$. For the calculation of the width of the radial basis function, two questions should be considered. First of all, the width value can not be too small, because the small width will cause a small degree of overlap. However, the degree of overlap can not be too large, because an over estimated behavior will be caused, which will greatly reduce the performance of the network. So, a new method to calculate the width of the radial basis function, which gives full consideration of the specific data distribution of each class, is proposed in this paper. A threshold value of membership degree is selected, and a credible selection is $\xi = 0.001$[19]. Then the samples of each class are re-screened and expressed using Equation (18).

$$G_i = \{x_k \in C_i : u_{ik} \ge \xi \in (0,1)\} \tag{18}$$

Next, the maximum distance from the cluster center to the sample of the G_i cluster is obtained:

$$d_{\max}^{i} = \max_{x_k \in G_i}\left\{\left\|x_k - v_i\right\|^2\right\} \tag{19}$$

Finally, the width σ_i yields:

$$\sigma_i = \frac{2d_{\max}^{i}}{3} \qquad (1 \le i \le c) \tag{20}$$

Thus, the value of RBFNN is obtained by the following equation.

$$g_i(x_k) = \exp\left(-\frac{\| x_k - v_i \|}{\sigma_i^{\,2}} \right) \tag{21}$$

The value of the radial basis function is matrix H, which is solved by substituting the cluster center and the width above into Equation (21). Apparently, H is $n \times c$, where n is the total number of samples, and c is the number of clusters.

For the solving of the weight, assume the output of the training samples is Y, the actual output of the network is $\tilde{Y}$, then according to the training process of the weight, the following error function can obtain the minimum only under the proper weight w. An expression of the error function:

$$E(W) = \left\| \tilde{Y} - Y \right\|^2 \tag{22}$$

Here, the least squares method is adopted to solve the weight value which makes the error function to achieve the minimum value. The following weight calculation formula can be easily deduced:

$$w = [H^T H]^{-1} H^T Y \tag{23}$$

Where, $[H^T H]^{-1}$ represents the pseudo-inverse calculation of the matrix. The well trained RBNNN is as follows.

$$f(x_k) = y_k = \sum_{i=1}^{m} w_i g_i(x_k) \tag{24}$$

5. Simulation and Analysis on Fault Diagnosis

5.1. Fault Diagnosis Simulation Based on Improved RBFNN

A four-bus-bar system is used as the experimental system, and it is shown in Figure 2. The system is composed of bus bars B1~B4, a transformer T1, and four transmission lines L1 ~ L4. CB represents the circuit breaker, MB represents the main protection of the bus bar, ML is the main protection of the transmission line, BL is the backup protection of the transmission line, and MT is the main protection of the transformer. The values of condition attributes are “0”or “1”. “1” indicates that the closed circuit breaker is disconnected or in protective state, “0” represents that the circuit breaker is unchanged or protection is non-operation.

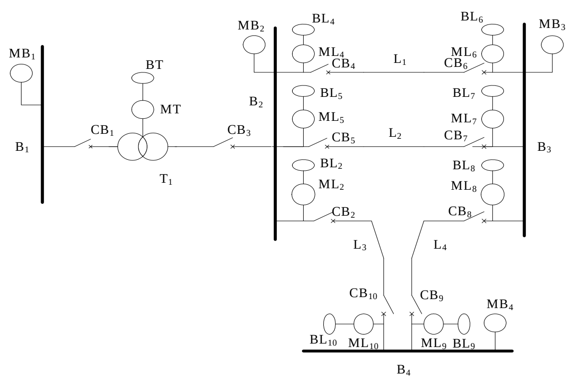

Figure 2. A Simple Power Grid Structure

39 samples are selected as a training sample set, so the input and output of the neural network are 39×16, 39×21, respectively. Set $\theta = 0.5$, randomly initialize the number of clusters and cluster centers, such as $C = 30$, and the diagnostic results are shown in Table 1. For these 39×16 -dimensional training input samples, we have the following description: each of this 16 -dimensional input signal represents the corresponding operation of the circuit breaker and the protection in the above figure, the order of the protection and circuit breaker in the input signal is as follows: ($CB_1, CB_2, CB_4, CB_5, CB_6, CB_7$, CB_{10}, MB_1, MT, ML_2, $ML_7, ML_8, ML_9, BL_4, BL_7, BT$) .Assume one of the input vector is ($1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0$), it represents that CB_1 and ML_7 have action, respectively. The dimension of the output training samples is 39×21, including single device fault and dual devices fault. If there is a fault of the device, the corresponding value takes “1”, otherwise, the value is “0”. There are 21 groups of input test samples, so the input test matrix is 21×16. Moreover, in order to detect the fault tolerance of the proposed algorithm, a new set of test samples is set by reversing all the action values of MB_1. Simulation results show that when the test samples are non-interference samples, accuracy of fault diagnosis is 100%. When the test samples with nosy, the output of the neural network is shown in Table 1, the correct fault diagnosis results have been marked with lines, only the sample 2 and the sample 10 can not correctly diagnosed in 21 group samples, apparently, accuracy of fault diagnosis is 90%.Particularly attention that sample 2 and sample 10 are complementary, so when disturbed, neither samples are able to identify by any diagnostic methods [20]. If we do not consider these two situations, diagnostic accuracy is still 100%, much higher than the method in [20].

Table 1. Simulation Results of Fault Diagnosis Based on Improved RBFNN

Number	B_1	T	B_2	B_3	B_4	L_1	L_2	L_3	L_4	B_1,T	B_2,T
1	0.1991	-0.0245	-0.0126	-0.0163	-0.015	0.0284	0.0336	-0.0026	-0.0229	0.0249	-0.0171
2	0.0023	0.0226	0.0122	0.0163	0.014	-0.012	-0.0294	0.0208	-0.0016	0.0208	0.0264
3	-0.2193	-0.059	-0.0446	0.0113	-0.0274	-0.0602	-0.091	0.1153	0.3673	0.1782	0.0382
4	-0.0908	0.1005	0.1083	-0.0361	0.0161	0.0187	-0.0035	-0.0308	-0.007	0.0169	-0.0406
5	-0.1533	0.0373	-0.0283	-0.0267	-0.0185	0.0292	-0.1169	-0.1155	0.1816	-0.0394	-0.033
6	-0.3025	0.0626	-0.0382	0.0566	-0.0432	0.0294	-0.0674	0.0104	0.1043	-0.1172	-0.0305
7	-0.2617	-0.0652	-0.059	-0.0046	-0.0939	0.0458	0.0251	-0.0838	0.0968	-0.1278	-0.028
8	-0.2145	0.0719	0.0341	-0.013	0.0486	0.0352	-0.1075	-0.0204	0.1728	-0.1291	-0.0385
9	-0.155	0.0633	-0.0382	0.0265	-0.0218	0.0158	-0.129	-0.0553	0.1975	-0.0287	-0.0171
10	0.0073	-0.0067	-0.0195	-0.0092	-0.0301	0.0088	0.0098	-0.012	0.0056	-0.0016	-0.016
11	0.1239	0.0692	0.0432	0.02	0.0561	-0.0072	-0.1131	0.1115	0.1406	-0.032	1.0494
12	0.0629	0.0456	0.0839	-0.0024	0.0247	0.0204	0.0112	0.0415	0.1614	0.7472	0.0071
13	0.1119	0.166	0.0114	0.0611	0.0199	0.0614	-0.1401	0.055	1.1083	-0.0673	0.0234
14	0.0498	0.0224	0.0195	-0.044	0.0661	0.0681	-0.0804	1.0788	0.1798	-0.1002	0.0182
15	0.0964	0.4742	0.0483	0.0828	-0.0363	0.042	0.6092	0.1391	0.0176	0.1134	0.0228
16	0.0031	0.0654	-0.0024	0.0553	0.0697	1.1067	-0.087	0.0521	0.1154	-0.0077	0.0112
17	0.0737	0.1311	-0.0312	0.0344	0.9908	0.0801	-0.2165	0.0435	0.171	0.0299	0.0191
18	0.0329	0.0401	-0.0127	1.0705	0.0629	0.0736	-0.0553	-0.0394	0.1044	0.0304	0.0023
19	0.0774	0.0582	1.0167	0.0553	0.0229	0.0046	-0.0157	0.0093	0.0519	0.0751	0.0002
20	0.1165	0.5958	0.0873	-0.0187	0.0653	-0.0149	0.4101	-0.0057	0.1586	-0.0104	-0.0193
21	0.8054	-0.0106	0.0251	0.0278	0.0744	-0.0311	-0.0078	0.0384	0.0407	0.0518	-0.0104

Table 1. Simulation Results of Fault Diagnosis Based on Improved RBFNN (continued)

序号	B_2,L_1	B_2,L_2	B_2,L_3	L_1,L_2	L_2,L_3	L_3,L_4	L_2,L_4	B_3,L_4	B_3,L_1	NO
1	-0.1692	0.0365	-0.1263	0.2161	-0.3115	0.0948	0.0103	-0.0287	0.2784	0.8245
2	0.6837	-0.0409	0.0134	-0.1186	0.0964	-0.0172	0.012	-0.0352	0.2427	0.0713
3	0.2631	0.0292	0.0379	-0.1149	0.0819	0.022	0.1863	0.4587	-0.3363	0.1633
4	0.3089	-0.0748	0.0308	-0.0548	0.0749	-0.0086	0.7118	0.1199	-0.3114	0.1516
5	0.3246	0.1079	0.2568	-0.0863	0.0753	0.4628	0.0802	0.2216	-0.3468	0.1876
6	0.3882	-0.0003	0.1394	-0.0125	0.8084	-0.0377	0.109	0.1821	-0.3954	0.1547
7	0.1716	0.128	0.0873	0.6047	0.2277	-0.0835	0.1133	0.3049	-0.2241	0.2263
8	0.2788	-0.0781	0.7449	-0.0686	0.0997	0.0395	0.0972	0.1456	-0.2992	0.2005
9	0.302	0.6507	0.1022	-0.1124	0.0427	-0.1141	0.326	0.1045	-0.3355	0.1758
10	0.2427	0.0611	-0.0129	0.0819	-0.0755	-0.0038	0.0026	0.0133	0.8094	-0.0551
11	0.4029	-0.1669	-0.0839	-0.2815	-0.0434	0.1132	0.1239	-0.1066	-0.5055	0.0861
12	0.33	-0.1502	-0.0333	-0.284	-0.1999	0.0018	0.1295	0.2325	-0.3593	0.1293
13	0.2788	-0.1554	-0.0524	-0.3219	-0.1005	0.0391	0.0658	0.0534	-0.3151	0.0971
14	0.323	-0.1007	-0.2273	-0.2907	-0.0764	0.1147	0.191	0.0402	-0.3554	0.1034
15	0.2905	-0.1116	-0.1179	-0.2731	-0.2478	0.1681	-0.0558	-0.0146	-0.3241	0.0769
16	0.2657	-0.1668	-0.2331	-0.3389	0.0323	0.1277	0.1727	-0.0401	-0.2934	0.0921
17	0.3287	-0.2186	-0.1654	-0.2579	-0.0731	-0.0786	0.3863	0.0237	-0.3692	0.098
18	0.316	-0.2758	-0.0419	-0.3878	0.0537	0.12	0.1343	0.0195	-0.3306	0.0828
19	0.335	-0.2178	-0.006	-0.2323	-0.0013	0.0062	0.0267	-0.0072	-0.3552	0.0961
20	0.3517	-0.1337	0.0109	-0.382	0.1828	0.0506	-0.0197	-0.1794	-0.3413	0.0954
21	0.0023	-0.1119	-0.0635	0.1268	0.0292	0.2151	-0.024	-0.1926	0.0073	0.0077

5.2. Comparison between FCM and the New Method

FCM is adopted to train RBFNN, and test results are compared with the results simulated by the improved method. Also select the number of clusters C = 30, simulation results are shown in Table 2. From Table 2, the fault diagnosis accuracy of RBFNN based on FCM is 85%, that is in 21 groups of samples, only 15 groups of diagnosis is correct.

Table 2. Simulation Results of Fault Diagnosis of RBFNN Based on FC

序号	B_1	T	B_2	B_3	B_4	L_1	L_2	L_3	L_4	B_1,T	B_2,T
1	0.0376	0.0105	0.0529	-0.0491	-0.0372	0.0269	0.025	0.0132	-0.0397	-0.0262	-0.0153
2	0.0374	0.0031	-0.0187	0.0318	0.0209	-0.0101	-0.032	-0.0456	-0.0534	-0.0282	0.1933
3	0.0114	-0.1069	-0.0763	0.0478	-0.0151	-0.0165	-0.0441	0.1828	0.1758	0.2316	0.0355
4	0.0713	0.014	0.2555	0.0089	-0.048	0.0703	0.0309	-0.0007	-0.0211	0.1185	-0.1321
5	0.0884	-0.0335	-0.09	-0.0441	0.0042	0.0419	-0.1448	-0.0807	0.1461	0.1327	-0.1111
6	0.0309	-0.1946	-0.0391	0.1521	-0.0417	-0.0411	-0.0461	0.0932	0.0041	0.1138	-0.0537
7	0.1123	-0.2232	0.0035	0.1154	-0.0491	-0.0011	-0.03	0.1339	-0.1001	0.1447	-0.1171
8	0.106	-0.0045	-0.0451	0.0086	0.1434	0.0765	-0.1052	0.1109	0.02	0.0142	-0.173
9	0.0257	-0.0098	-0.0711	0.0309	0.112	-0.0422	-0.0357	-0.0057	0.0066	0.0909	-0.0558
10	0.058	0.0302	0.0291	-0.0116	-0.0059	-0.0257	-0.0044	-0.084	-0.0645	-0.1007	0.2958
11	-0.1137	-0.0704	-0.0607	0.0272	0.0303	0.0287	0.0146	0.1522	0.125	0.2013	0.4311
12	-0.0942	-0.0367	-0.0138	-0.0589	0.0407	0.0314	0.1061	0.1699	0.005	0.523	0.0295
13	-0.0379	0.1285	-0.1082	0.1661	-0.0312	0.1556	0.0373	0.0406	0.4323	0.0657	0.01
14	-0.0716	-0.1051	-0.0655	0.0199	0.1636	0.1549	0.0327	0.4302	0.0123	0.2028	0.0155
15	-0.0739	0.2076	0.0096	0.1399	-0.0036	0.106	0.2601	0.0955	0.0895	0.2116	-0.0681
16	-0.0915	0.006	-0.0776	0.1205	0.1424	0.44	0.062	0.1767	0.1548	0.0908	-0.0899
17	-0.0732	-0.0311	0.0561	0.1256	0.3619	0.1309	-0.0554	0.1741	-0.051	0.084	-0.0938
18	-0.0112	-0.0025	0.1209	0.4426	0.1131	0.0883	0.0533	0.015	0.131	-0.0313	-0.1238
19	-0.0017	0.0001	0.3961	0.2223	0.1309	-0.013	0.0279	0.018	-0.0404	0.1095	-0.1203
20	-0.0208	0.3913	-0.0226	0.0804	0.0215	0.0475	0.2019	-0.043	0.1777	0.0668	-0.1521
21	0.1842	-0.0054	0.0156	0.0063	-0.0517	-0.0733	-0.0588	-0.0517	-0.0212	-0.0766	-0.0938

Table 2. Simulation Results of Fault Diagnosis of RBFNN Based on FCM (continued)

序号	B_2,L_1	B_2,L_2	B_2,L_3	L_1,L_2	L_2,L_3	L_3,L_4	L_2,L_4	B_3,L_4	B_3,L_1	NO
1	0.0116	0.0482	-0.0107	0.0397	-0.0883	0.108	0.2865	-0.189	0.0469	0.7487
2	0.4919	-0.0476	-0.0193	0.0956	0.0047	-0.0088	-0.1424	0.0664	0.2808	0.1802
3	0.1699	0.0612	-0.2329	0.0833	0.3119	-0.0015	-0.3405	0.491	-0.2363	0.2679
4	0.1656	-0.2361	-0.1212	0.0522	0.0141	0.105	0.2026	0.236	-0.0706	0.2851
5	0.2135	0.2137	0.0387	0.0599	0.0073	0.33	-0.2058	0.3092	-0.1408	0.2649
6	0.1676	-0.098	0.0341	0.3773	0.4729	-0.1553	-0.3409	0.39	-0.1703	0.3451
7	0.2245	-0.0964	-0.2123	0.607	0.2325	0.0018	-0.1392	0.3011	-0.1369	0.2289
8	0.2632	-0.0806	0.4515	0.0627	0.1226	-0.0774	-0.2249	0.2211	-0.1224	0.2322
9	0.099	0.5487	-0.1736	0.1179	-0.0903	0.0483	-0.1565	0.3072	-0.0977	0.3511
10	0.2808	-0.0086	0.1375	0.0753	-0.0037	0.0649	0.1467	-0.1513	0.4321	-0.0899
11	0.4022	-0.0065	-0.2665	-0.1144	-0.0171	-0.1329	-0.2933	0.3178	0.1487	0.1964
12	0.1932	0.0361	-0.3406	0.0626	0.2426	-0.0028	-0.2676	0.3828	-0.2502	0.2417
13	0.1785	-0.004	-0.199	0.0216	0.0138	0.0029	-0.3902	0.4511	-0.2197	0.286
14	0.1642	-0.1786	0.1269	0.01	0.1911	-0.1967	-0.3107	0.3523	-0.2276	0.2791
15	0.2087	-0.2023	-0.3229	0.2416	0.2287	-0.2165	-0.2218	0.2282	-0.1639	0.2458
16	0.2138	-0.2171	0.1864	0.237	-0.4928	0.0171	-0.2303	0.246	-0.1778	0.2834
17	0.2242	0.4747	0.2519	-0.1618	-0.0953	-0.107	-0.4238	0.1315	-0.1494	0.227
18	0.2627	0.3066	-0.3378	0.3919	-0.0183	-0.2393	-0.4729	0.2443	-0.1695	0.237
19	0.2112	0.2379	-0.285	-0.098	0.0677	-0.1407	-0.1072	0.2452	-0.1276	0.2671
20	0.2426	-0.0986	-0.1024	-0.0595	0.3378	-0.1097	-0.2674	0.1727	-0.1293	0.2651
21	0.0374	0.0604	0.1749	0.2784	0.3204	0.1918	0.1211	0.011	0.0581	-0.0266

6. Conclusion

In this paper, a new hybrid fuzzy clustering algorithm is proposed to optimize the parameters of the RBFNN, and it is applied to the fault diagnosis of power grid. Simulation results show that the method in this paper reduces the influence of the clustering initial choice to the diagnostic results, and improves the convergence speed and accuracy of RBFNN. It has validity for power grid fault diagnosis, especially for the noise disturbance, such as switching or protecting malfunction, it has high robustness. This method has a practical significance for the fast and accurate fault diagnosis, and the enhancement of supply reliability.

References

[1] Wang Jialin, Xia Li, Wu Zhengguo, et al. State of arts of fault diagnosis of power system. *Power System Protection and Control*. 2010; 38(18): 210-216 (in Chinese)

[1] Cardosog Jr, Rolimig. Application of neural-network modules to system fault section estimation. IEEE Trans on Power Delivery. 2004; 19(3): 1034-1041.

[2] Guo Chuangxin, Zhu Chuanbai, Cao Yijia, et al. State of arts of fault diagnosis of power systems. *Automation of Electric Power Systems*. 2006; 30(8): 102-107 (in Chinese)

[3] Bi Tianshu, Ni Yixin, Yang Qixun. An evaluation of artificial intelligent technologies for fault diagnosis in power network. *Automation of Electric Power Systems.* 2000; 24(2): 11-16 (in Chinese)

[4] Lin Sheng, He Zhengyou, Qiang Qingquan. Review and development on fault diagnosis in power grid. Power System Protection and Control. 2010; 38(4): 140-150 (in Chinese)

[5] Chen Yulin, Chen Yunping, Sun Jinlin, et al. A survey of power system fault diagnosis. Electric Power. 2006; 39(5): 27-31 (in Chinese)

[6] Li Xiaoquan, Zhuang Dehui, Zhang Qiang. A new fault diagnosis model of electric power grid based on rough radical basis function neural networks. Power System Protection and Control. 2009; 37(18): 20-24 (in Chinese)

[7] Bi Tianshu, Ni Yixin, Wu Fuli, et al. *A novel neural network approach for fault section estimation*. Proceedings of the CSEE. 2002; 22(2): 73-78 (in Chinese)

[8] Antonios D. Niros, George E Tsekouras. *A novel training algorithm for RBF neural network using a hybrid fuzzy clustering approach*. Fuzzy Sets and Systems. 2011; 8: 1-20.

[9] SB Roh, TC Ahn, W Pedrycz. The design methodology of radial basis function neural networks based on fuzzy K-nearest neighbors approach. *Fuzzy Sets Syst.* 2010; 161(13): 1803–1822.

[10] Sun Dan, Wan Liming, Sun Yanfeng, et al. An improved hybrid learning algorithm for RBF neural network. *Journal of Jilin University (Science Edition).* 2010; (5): 17-822 (in Chinese)

[11] Wang Liang, Wang Shitong. Mercer kernel based hybrid C-means fuzzy clustering algorithm with dynamic weight. *Application Research of Computers.* 2011; 28(8): 2852-2855 (in Chinese)

[12] H Sarimveis, oganis, Alexandridis. A classification technique based on radial basis function neural networks. *Adv. Eng. Software.* 2006; 7(4): 218–221.

[13] Geweniger T, Zulke D, Hammer B, et al. Median fuzzy c-means for clustering dissimilarity data. *Neurocomputing*. 2010; 73(1): 1109-1116.

[14] Li Peingqiang, Li Xinran, Chen Huihua, et al. *The characteristics classification and synthesis of power load based on fuzzy clustering*. Proceeedings of the CSEE. 2005; 25(24): 73-78 (in Chinese)

[15] GE Tsekouras, D Darzentas, I. Drakoulaki, et al. Fast fuzzy vector quantization. IEEE International Conference on Fuzzy Systems, Barcelona. 2010.

[16] Li Guanlin, Ma Zhanhong, Huang Chong, et al. Segmentation of color images of grape diseases using K_means clustering algorithm. Transactions of the CSAE. 2010; 26(Supp.2): 32-37 (in Chinese)

[17] Jiang Huilan, LiuXiaojin, GuanYing, et al. Short-term load forecasting based on Hard-C mean clustering algorithm and support vector machine. Power System Technology.

[18] AD Niros, GE Tsekouras. On training radial basis function neural networks using optimal fuzzy clustering. 17th IEEE Mediterranean Conference on Control and Automation, Mediterranean. 2009.

[19] Qian Tao. Application and Research in Distribution Network Fault Diagnosis by Rough Set Theory and Neural Network. Nanjing: Nanjing University of Science and Technology. 200.