Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

APPLICATION OF RBF NEURAL NETWORK IMPROVED BY PSO ALGORITHM IN FAULT DIAGNOSIS

[1] LIN CUI, [2] CAIYIN WANG, [1] BAOSHENG YANG

[1] School of Information Engineering, Suzhou University, Suzhou 234000, Anhui, China

[2] School of Mechanical Electric and Engineering, Suzhou University, Suzhou 234000, Anhui, China

ABSTRACT

The current fault diagnosis methods based on conventional BP neural network and RBF neural network exist long training time, slow convergence speed and low judgment accuracy rate and so on. In order to improve the ability of fault diagnosis, this paper puts forward a kind of fault diagnosis method based on RBF Neural Network improved by PSO algorithm. By using particle swarm algorithm's heuristic global optimization ability, the connection weight values of RBF neural network are optimized. And then combined with RBF neural network's nonlinear processing ability, transformer fault samples are trained and tested. The experimental results show that, compared with conventional fault diagnosis methods based on BP neural network and RBF neural network, the method based on RBF Neural Network improved by PSO algorithm can effectively avoid the problems of RBF neural network's instability, RBF neural network easily falling into local minima and low correct diagnosis rate, which can effectively improve the convergence speed and the efficiency of fault diagnosis.

Keywords: *Particle Swarm Optimization Algorithm, RBF Neural Network, BP Neural Network, Transformer Fault Diagnosis*

1. INTRODUCTION

Nowadays, with the increasing complexity of control system structure, the fault diagnosis of nonlinear system has become a hot and difficult problem in today's fields of fault diagnosis; transformer fault diagnosis is one of them. Because neural network has the ability of good self-learning, parallelism, strong fault tolerance and generalization ability, without needing a precise mathematical model, a set of nonlinear mappings can be well achieved. Thus, neural networks are widely used in fault diagnosis. At present, the two types of feed-forward neural network, Back-propagation (BP) neural network and Radial Basis Function (RBF) neural network are widely used in fault diagnosis. But traditional BP neural network and its improved method have the shortcomings of local optimal solutions, slow training speed and low efficiency and so on, which limit the scope of application of BP neural network [1]. RBF neural network can solve these problems. RBF neural network has a higher computing speed, it can globally approximate to a nonlinear function with arbitrary precision, which has been widely used in many fields. However, in practical application of fault diagnosis, the output weight values, center value and width of the hidden unit of RBF neural network have a large impact on its performance. And parameters optimization algorithms of RBF neural network, gradient descent algorithm and genetic algorithm are not particularly desirable in parameter optimization results [2].

Particle Swarm Optimization (PSO) can be applied to solve the parameters optimization problem of RBF neural network. PSO algorithm is a new fast optimization method, which has fast convergence rate, high robustness, and strong global search capability and is easy to implement, etc [3]. PSO is used to optimize the RBF neural network's connection weight values, which not only can play the generalization ability of RBF neural network greatly, but also can improve the convergence speed and learning ability of RBF neural network.

In this paper, we propose the transformer fault diagnosis method based on RBF neural network improved by PSO algorithm, which makes full use of heuristics and global optimization ability of PSO algorithm. The total content percentage of oil dissolution characteristics gas in power transformers is regarded as RBF neural network's input. Output and input variance of RBF neural network are regarded as fitness functions. Through continuous iterations, the optimal solution is finally got, which is regarded as the input and output layer connection weights and thresholds of RBF neural

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

network. Compared with BP neural network and RBF neural network, the experiments show that our proposed method can optimize the weights and thresholds of RBF neural network, and can avoid falling into local minimal and instability, which can greatly improve the learning efficiency of RBF neural network.

2. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization (PSO) algorithm is a swarm intelligence optimization algorithm introduced by American psychologist James Kennedy and electrical engineer Russell Eberhart in 1995[4].The basic idea of PSO algorithm stems from simulation of the behavior of birds' predation and PSO is an optimization algorithm which utilizes the cooperation and competition of the groups particles to produce the optimal solution. When solving optimization problems, PSO algorithm regards the solution of each problem as search space of a bird, called a particle. Each particle has a fitness value determined by the optimized function and has a velocity to decide its flying direction and distance. Particles follow the current optimal particle for searching in the solution space. PSO algorithm first initializes a group of random particles (random solution), and then finds the optimal solution by iteration. During each of iteration, particles update their own by tracking the two extremums. The first extremum is the optimal solution found by the particle itself, which is regarded as its individual best position; another extremum is the optimal solution found by entire swarm, which is noted as the global best position [5].

The mathematical model of PSO algorithm is described as followings: Suppose that the particle population size is N, the goal search space is D-dimensional. The position vector of the i-th particle in D-dimensional space is $x_i = (x_{i1}, x_{i2}, \cdots, x_{ik}, \cdots, x_{iD})$, each x_i represents a potential feasible solution of search space. When putting x_i into the target function, its fitness value can be calculated, which can be used to judge whether the particle is good or not. The flight speed of the i-th particle is represented as a vector $v_i = (v_{i1}, v_{i2}, \cdots, v_{ik}, \cdots, v_{iD})$. The individual best position searched out by PSO is $P_i = (P_{i1}, P_{i2}, \cdots, P_{ik}, \cdots, P_{iD})$, and the global best position searched out by the entire particle swarm is $Q_i = (Q_{i1}, Q_{i2}, \cdots, Q_{ik}, \cdots, Q_{iD})$. When finding out two best values P_i and Q_i, each particle updates its own speed and location according to the following formulas. Iterative formula is as follows:

$$P_{i,t+1}^k = \begin{cases} x_{i,t+1}^k, f(x_{i,t+1}) < f(P_{i,t}) \\ P_{i,t}^k, else \end{cases} \quad (1)$$

$$v_{i,t+1}^k = \omega v_{i,t}^k + c_1 r_1 (P_{i,t}^k - x_{i,t}^k) + c_2 r_2 (Q_{i,t}^k - x_{i,t}^k) \quad (2)$$

$$x_{i,t+1}^k = x_{i,t}^k + v_{i,t+1}^k \quad (3)$$

Where, c_1 is a cognitive acceleration factor to adjust the step length of flight direction of individual optimal particle, c_2 is a social acceleration factor which is used to adjust the step length of flight direction of the global optimal particle. r_1 and r_2 are two random numbers between zero and one, and adding randomness makes search space be enlarged. $v_{i,t}^k$ and $x_{i,t}^k$ respectively denote the speed and position of the i-th particle of the k-dimensional in the t-th iteration, $P_{i,t}^k$ and $Q_{i,t}^k$ respectively denote the individual and global best position of the i-th particle of k-dimensional space in the t-th iteration. ω is the inertia factor, which can control the search speed and make particles converge to local minima quickly, and then get the final solution through local search. The updated formula of inertia factor ω is as follows:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) t / T_{\max} \quad (4)$$

3. STRUCTURE ANALYSIS OF RBF NEURAL NETWORK

In 1998, Broomhead and so on introduced Radial Basis Function (RBF) neural network. RBF neural network is a feed-forward and back-propagation neural network, including an input layer, a hidden layer and an output layer [6]. The network structure is shown in Figure 1. Nodes of the input layer simply pass input signals to the hidden layer, the hidden layer neurons produce nonlinear mapping by using radial basis function, and output layer neurons execute linear weighted combination to the output of the hidden layer.

Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

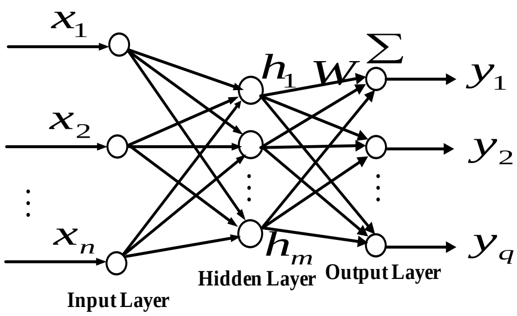

Figure 1: The Structure Of RBF Neural Network

As shown in Fig 1, $X=[x_1,x_2,\cdots,x_n]^T$ is an n-dimensional input vector, $H=[h_1,h_2,\cdots,h_m]^T$ is a radial basis direction vector of RBF network, which represents the output of the hidden layer unit and usually is expressed by using Gaussian function, which is given by:

$$h_i(x)=\exp\left(-\frac{\|X-C_i\|}{2b_i^2}\right)\quad i=1,2,\cdots,m \qquad (5)$$

Where, C_i represents the center of the i-th basis function, b_i represents the width of the i-th basis function, and b_i is a number greater than zero, $\|\bullet\|$ is the Euclidean norm, m represents the number of nodes of the hidden layer. $W=[w_1,w_2,\cdots,w_m]^T$ is a weight vector of RBF network. The output of RBF neural network is linear combination of the output of the hidden layer nodes, which is expressed as:

$$y_k(x)=\sum_{k=1}^{q}W_{ik}h_i(x) \qquad (6)$$

Where, $k=1,2,\cdots,q$. q is the number of nodes of the output layer. W_{ik} represents the connection weight values between the i-th hidden layer nodes and the k-th output nodes.

Two categories of parameters need to be determined in RBF neural network [7]: the first category parameters are the center C_i, the width b_i and the number of centers n of radical basis function; another category parameters are connection weight values between the output layer and the hidden layer. After the center C_i , the width b_i , and the number of centers n of radical basis function are determined, we can obtain the connection weight values between the output layer and the hidden layer by using the least squares method. Therefore, determining C_i , b_i and n of radical basis function is the key to establish RBF neural network.

4. STEPS OF PSO OPTIMIZING RBF NEURAL NETWORK

Now, we understand that RBF neural network's performance mainly depends on the center and the width of radical basis function of the hidden layer and the weight values of the output layer. Traditional RBF neural network learning strategy has significant drawbacks, which only finds the optimal solution in local space to determine the network structure parameters. If these parameters are set incorrectly, it would cause decline in the approaching accuracy and even produce network divergence [8]. PSO algorithm has fast convergence speed, strong global search capability and does not require gradient information and so on, which can improve convergence speed and stability of RBF neural network. Therefore, in this paper, we utilize PSO algorithm to optimize the traditional RBF neural network learning strategy. The learning process based on RBF neural network improved by PSO is described as followings:

(1) Pretreatment the transformer's original fault data sample. The collected raw data are divided into two parts, training set and test set. Training set is used to create a fault model; test set is used to verify the validity of the model.

(2) Utilize RBF neural network to learn the training set. During the learning process, using PSO to optimize parameter, the parameter optimization process is as follows:

(a) Initialize particle swarm and RBF neural network. The population size N , search space dimension D and acceleration coefficients c_1 and c_2 of particle swarm should be determined. According to the formula (2), (3) and (4), particle velocity $v_{i,1}^k$, position $x_{i,1}^k$ and inertia factor ω are also initialized. The maximum value of speed and the maximum value of position are set to meet $V_{\max}=X_{\max}$. The minimum error and the maximum number of iterations T are also decided. RBF neural network should also be initialized, including the numbers of input and output and the number of centers of radical basis function. The center C_i, the width b_i, and the number of centers nodes n of radical basis function are combined into a particle.

Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(b) Select the individual best position of each particle P_i and the global best position of particle swarm Q_i. Individual fitness value of each particle is calculated according to the formulas (1) and (3).The inertial factor ω is updated according to the formula (4). According to the formula (2) and (3), speed and position are also updated. Judging whether the particle velocity and position exceed the maximum value, if exceed the maximum value, the particle velocity and position should be adjusted.

(c) Judge whether to arrive at the maximum number of iterations or meet the requirements of the minimum error, if it is, the iteration should be stopped. The global optimal values are regarded as weights and thresholds of RBF neural network, otherwise, return to (b).

(d) The decoded value of the best position experienced by particle swarm is looked upon as the structural parameters of RBF neural network, then training samples are trained and their mean square error on training set are calculated out.

(e) Evaluate search position of each particle according to the mean square error to find the optimal parameters, and establish the optimal model of RBF neural network.

(3) Utilize the established RBF neural network model to execute fault diagnosis to the test set, and lastly obtain diagnosis results.

Specific learning process is shown in Figure 2.

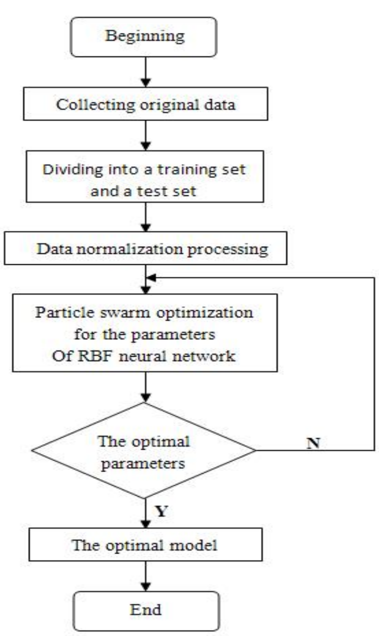

Fig 2: Flow Chart Of Establishing The Optimal RBF Neural Network Model

5. SIMULATION VERIFICATION

5.1 Experimental Principle

Consulting the relevant references[9]-[10], we know that according to the cause of faults and the extent of the damage of transformers, the common transformer faults can be divided into five types that are normal, low-mid temperature overheating (low temperature overheating, mid temperature overheating), high temperature overheating, low energy discharge and high energy discharge. When various transformers faults happen, H_2, CH_4, C_2H_6,C_2H_4 and C_2H_2 in transformer oil share of different ingredients, thus we can determine what kind of fault occurs according to the gases decomposition in transformer oil.

5.2 Experimental Data and Parameters

To verify the effectiveness of our proposed method based on RBF neural network improved by PSO algorithm (PSO-RBF), we adopted fault samples of Reference [11] as the experimental data set. Among 150 fault data samples, the top 100 were used for training; the last 50 were used to test. Training samples were processed and the processing results are shown in Table 1. Input variables X_i (i = 1, 2, …, 5) respectively represent the percentage of the total gas content occupied by the content of H_2, CH_4, C_2H_6,C_2H_4 and C_2H_2 . The output fault types Y_i (i = 1, 2, …, 5)respectively denote normal, low-mid temperature overheating, high temperature overheating, low energy discharge and high energy discharge. As can be seen from Table 1, there is a complex nonlinear relationship between the composition of gases dissolved in transformer oil and fault types.

Table 1 : The Original Fault Samples

No.	X_1	X_2	X_3	X_4	X_5	Y_1	Y_2	Y_3	Y_4	Y_5
1	0.4977	0.0845	0.0215	0.1935	0.2028	0	0	0	0	1
2	0.4479	0.1749	0.0364	0.2356	0.1052	0	0	0	0	1
3	0.6139	0.1082	0.0416	0.1041	0.1322	0	0	0	1	0
4	0.5798	0.1887	0.0462	0.0866	0.0987	0	0	0	1	0
5	0.0469	0.1083	0.1752	0.6696	0.0000	0	0	1	0	0
6	0.0376	0.2682	0.0722	0.6189	0.0031	0	0	1	0	0
7	0.4026	0.2511	0.1861	0.1602	0.0000	0	1	0	0	0
8	0.3356	0.3356	0.0923	0.2349	0.0015	0	1	0	0	0
9	0.3366	0.0297	0.3317	0.2772	0.0248	1	0	0	0	0
10	0.4202	0.3361	0.1485	0.0896	0.0056	1	0	0	0	0

5.3 Simulation Results and Analysis

Under the Windows XP operating system, using Matlab 2007 toolbox, PSO algorithm was used to train RBF neural network with training sample.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Firstly, RBF neural network model was initialized, the number of input variables i_1 and the number of output fault types i_2 are both 5, the number of centers of radical basis function n is equals to 10. The population size of Particle Swarm N is equals to 30, the number of parameters to be optimized $D = i_1 \times n + i_2 \times n + n + i_2 = 115$, D is search space dimensions, the acceleration coefficient c_1 = c_2 = 2.0, the inertia factor is 0.712, the speed and position of the maximum value were set to meet $V_{\max} = X_{\max}$, and the maximum number of iterations were set to T = 2 000. Training results are shown in Figure 3.

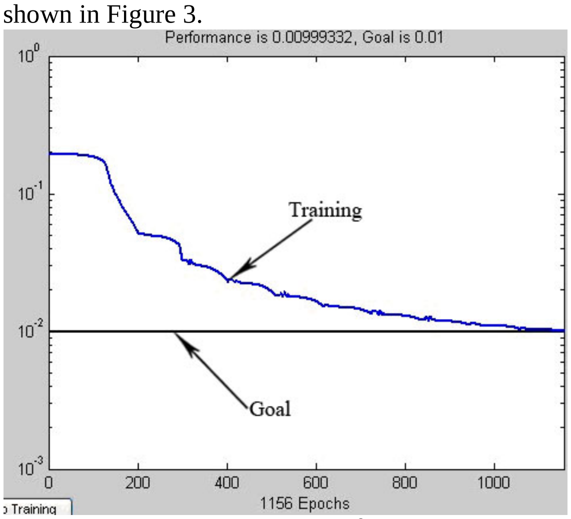

Fig 3: Training Error Curve Of PSO-RBF Neural Network

To verify the effectiveness of our proposed PSO-RBF algorithm, adopting the same fault samples, we respectively trained and tested the conventional RBF neural network and BP neural network. Training results are shown in Figure 4 and Figure 5.

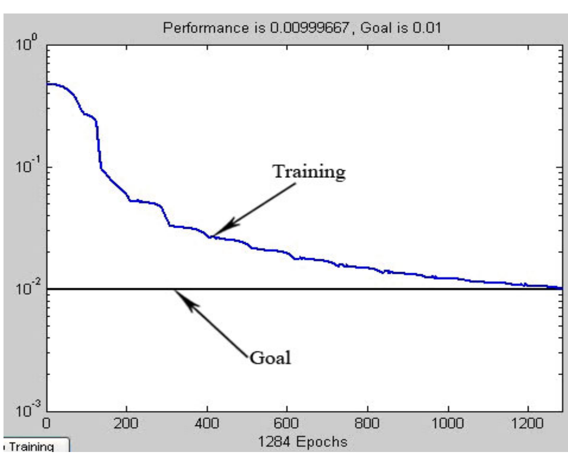

Fig 4: Training Error Curve Of RBF Neural Network

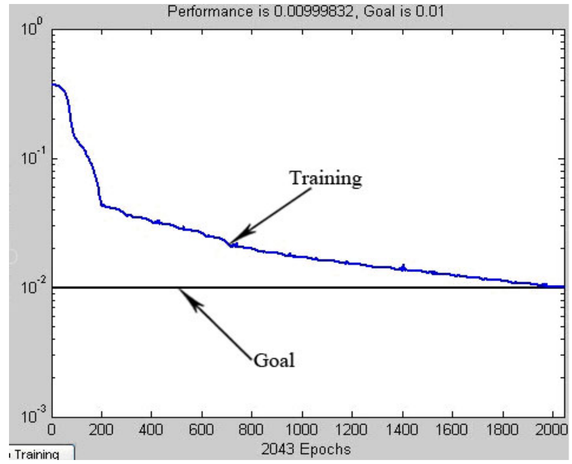

Fig 5: Training Error Curve Of BP Neural Network

As can be seen from Figure 3, Figure 4 and Figure 5, PSO-RBF neural network has a faster convergence speed than traditional RBF neural network and BP neural network. Because each training result was unstable, we respectively took training 100 times and then calculated average convergence steps for the three methods. The training and test results of the three algorithms are as shown in Table 2.

Table 2 : Results Of Training And Test

Algorithm	Average convergence steps	Convergence success rate	Correct rate
PSO-RBF	1156	97%	96%
RBF	1284	94%	94%
BP	2043	90%	86%

As can be seen from Table 2, the average convergence step of PSO-RBF neural network is 1156, while the average convergence step of RBF neural network is 1284 and the average convergence step of BP neural network is 2043, PSO-RBF neural network has the smallest average convergence steps. Convergence success rate of PSO-RBF was also much more greatly improved than convergence success rates of RBF neural network and BP neural network, which effectively improved RBF network's convergence speed and stability. In the fault diagnosis results of PSO-RBF neural network, there only appeared to be a wrong judgment and a case not in full compliance with the model, in addition, simulation results basically conformed to the actual faults and the correct rate arrived at 96%. RBF neural network model judged wrongly once, two cases does not fully meet the actual fault types; the correct rate is 94%. BP network model judged wrongly three times, four cases does not fully meet the actual fault types and the correct rate is only 86%. The experimental

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

results show that our proposed PSO- RBF model has a higher convergence rate and a higher fault diagnosis accuracy to fault diagnosis of power transformers.

6. CONCLUSION

This paper takes full advantage of PSO algorithm to optimize the center value and width of RBF neural network and weight values from the hidden layer to the output layer. The optimized neural network was used for transformer fault diagnosis. Simulation results show that compared with the other two fault diagnosis methods based on conventional RBF neural network and BP neural network, RBF neural network improved by PSO algorithm obtains faster convergence speed and higher convergence success rate, and the correct rate of transformer fault diagnosis is effectively improved and the effect is very obvious.

ACKNOWLEDGEMENTS

This work was supported by Project of Anhui Province Natural Science Foundation of China (No. 10040606Q64) and Ordinary Project of Anhui Province Colleges and Universities Natural Science Foundation of China (No.KJ2011B173) and Open Project of Intelligent Information Processing Lab at Suzhou University of China (No.2012YKF36).

REFERENCES:

[1] G.L. Wang, J.H. Wu, S.F. Yin, L.Q. Yu, J. Wang, "Comparison between BP neural network and multiple linear regression method" , Proceedings of the First International Conference on Information Computing and Applications (Page:365-370 Year of Publication:2010 ISBN: 3-642-16166-9).

[2] D.J. Du, K. Li, M.R. Fei, "A fast multi-output RBF neural network construction method", *Neurocomputing*, Vol. 73, No. 10, 2010, pp. 2196-2202.

[3] H. Modares, A. Alfi, M.N. Sistani, "Parameter estimation of bilinear systems based on an adaptive particle swarm optimization", *Engineering Applications of Artificial Intelligence*, Vol. 23, No. 7, 2010, pp. 1105-1111.

[4] S. Solomon, P. Thulasiraman, R. Thulasiram, "Collaborative multi-swarm PSO for task matching using graphics processing units", Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation(Page:1563-1570 Year of Publication:2011 ISBN: 978-1-4503-0557-0).

[5] A.W. Mohemmed, M. Zhang, W. N. Browne, "Particle swarm optimisation for outlier detection", Proceedings of the 12th Annual Conference on Genetic and Evolutionary Computation (Page:83-84 Year of Publication:2010 ISBN: 978-1-4503-0072-8).

[6] O.P. Sangwan, P.K. Bhatia, Y.Singh, "Radial basis function neural network based approach to test oracle", *ACM SIGSOFT Software Engineering Notes*, Vol. 36, No. 5, 2011, pp. 1- 5.

[7] H.G. Han, Q.L. Chen, J.F. Qiao, "An efficient self-organizing RBF neural network for water quality prediction", *Neural Networks*, Vol. 24, No. 7, 2011, pp. 717-725.

[8] Z.F. Chen, P.D. Qian, Z.F. Chen, "Application of PSO-RBF neural network in network intrusion detection", Proceedings of the 3rd International Conference on Intelligent information Technology Application(Page:362-364 Year of Publication:2009 ISBN: 978-1-4244-5212-5).

[9] J.P. Shi, W.G. Tong, D.L. Wang, "Design of the Transformer Fault Diagnosis Expert System Based on Fuzzy Reasoning", Proceedings of the 2009 International Forum on Computer Science-Technology and Applications (Page: 110-114 Year of Publication: 2009 ISBN: 978-0-7695-3930-0).

[10] A. Shintemirov, W. Tang, Q.H. Wu, "Power transformer fault classification based on dissolved gas analysis by implementing bootstrap and genetic programming", *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, Vol. 39, No. 1, 2009, pp.69-79.

[11] L. Li, Y.P. Ni, J.Y. Sun, "Research of Transformer Fault Diagnosis Based On Improved Particle Swarm Algorithm", *Control and Instruments in Chemical Industry*, Vol. 37, No. 7, 2010, pp.43-46.