Journal of Management Science and Statistical Decision
Vol.7 No1.(2010) p118-121

# Application of RBF Neural Network Optimized by PSO Algorithm on Condition-based Maintenance of Transmission and Transformation Equipments

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***Abstract*—In this paper, an improved neural network algorithm is used in the fault diagnosis for transmission and transformation equipments. In the process of model building, Particle Swarm Optimization (PSO) algorithm is used to optimize the Radial Bases Function (RBF) neural network. By controlling the bias of diagnosis results, the network parameters are adjusted dynamically and then the network structure is optimized and the diagnostic accuracy is raised. The correctness and effectiveness of this algorithm are proved by means of practical example in voltage transformer DGA fault diagnosis. It can also be used in fault diagnosis among kinds of other transmission and transformation equipments.**

***Keywords-RBF nueral network; PSO; fault diagnosis; Condition-based maintenance; voltage transformer***

## I. INTRODUCTION

Condition-based Maintenance (CBD) belongs to the scope of Predictive Maintenance [1]. Its arrangements and implementations depend on equipment conditions. Accordingly, on the basis of existing monitoring techniques, how to make full use of databases, data mining and other information technologies to diagnose faults and to determine operating states is the focus of study on CBD.

At present, extensive researches are carried out in the study of transmission and transformation equipments fault diagnosis models, and fruitful results have been yielded. Of these, for its self-adaptability, self-learning, fault tolerance, non-linear mapping features and strong learning ability, memory capacity, associative ability and recognition capacity, artificial neural network accesses to a wide range of applications of fault diagnosis in electrical equipment [2-5].

RBF neural network is a kind of feed-forward neural network with good generalization, approximation capability and less calculation amount which has been widely used in pattern recognition, function approximation, adaptive filtering and so on. In this paper, a method of RBF neural network model optimized by PSO algorithm is introduced. In the empirical analysis, the diagnosis model will be designed integrated with the Dissolved Gases Analysis (DGA) of voltage transformer.

## II. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

Particle swarm optimization (PSO) algorithm is derived from the simulation of the flock feeding behavior. It is an evolutionary computing technique based on swarm intelligence. PSO algorithm not only has the global optimization capacity, at the same time, also has strong local optimization ability by adjusting the parameters. Because its parameter adjustment is simple, moreover, it can quickly converge to the optimal solution, PSO algorithm is more suitable for computer programming. Further more, PSO algorithm can avoid the degradation caused by full optimization [6]. Because of its simple, effective features, PSO algorithm has been widely used in function optimization, neural network training, pattern classification, fuzzy system control and other fields. This paper will use it to optimize the parameters of RBF function.

### *A. The principle of PSO algorithm*

PSO algorithm is an evolutionary algorithm for global optimization, invented by Dr. Eberhart and Dr. Kennedy [7]. The algorithm is derived from the simulation of flock feeding behavior. In the particle swarm algorithm, the solution of each optimization problem is a bird in the searched space. Each bird is seen as a particle which has no quality and size, and is extended to a D-dimensional space [8]. The location of particle $i$ in the D-dimensional space is expressed as a vector, its flight velocity is expressed as a vector, too. Every particle has a fitness value determined by a fitness function optimized. Besides, every particle has a velocity which determines their flight direction and distance. Each particle know the discovered best position so far (pbest) and the present position, this can be viewed as the particle's own searching experience. In addition, each particle also know the best position among the whole group (gbest is the best value of all the pbest values), this can be regarded as particles companion experience. Particles determine the next movement by their own experiences and the best experience among their companies.

### *B. The standard PSO algorithm flow[9]*

(1) Randomly initialize the positions and velocities of particles. Usually they are randomly generated in the extent permitted. Set current location coordinate to the pbest coordinate of each particle. Calculate corresponding individual extreme (i.e., individual fitness value). Global extreme (i.e., overall fitness value) is the best among all the individual extremes. Record its corresponding particle index, and set gbest as the current location of this particle.

(2) Calculate the fitness value of each particle.

(3) For each particle, compare its fitness value with the individual extreme, if better, update the current individual extreme.

(4) For each particle, compare its fitness value with the global extreme, if better, update the current global extreme.

(5) Update each particle's position and velocity, using the following formula:

$$\mathbf{v}_{id}(t+1) = \omega \mathbf{v}_{id}(t) + c_1 r_1 (\mathbf{p}_{id} - \mathbf{x}_{id}(t)) + c_2 r_2 (\mathbf{p}_{gd} - \mathbf{x}_{id}(t)) \quad (1)$$

$$\mathbf{x}_{id}(t+1) = \mathbf{x}_{id}(t) + \mathbf{v}_{id}(t+1) \quad (2)$$

Where, $\omega$ is inertia weight, affecting both global and local optimization capabilities, generally set its value 0.4-1.4; $c_1$and $c_2$ are called the acceleration coefficient ($c_1$, $c_2 > 0$), on behalf of the weight putting each particle into the individual and global extreme, generally take $c_1 = c_2$, and set the values 0-4; $\mathbf{v}_{id}(t)$ and $\mathbf{x}_{id}(t)$ are the current speed and location; $\mathbf{v}_{id}(t+1)$ is the velocity in the next moment of particle *i*; $\mathbf{p}_{id}$ and $\mathbf{p}_{gd}$ were individual best value and group best value particle *i* has experienced.

(6) If the predetermined criterion isn't meet, stop and then return to Step (2); if criterion is meet, stop the calculation.

## III. OPTIMIZATION OF RBF NEURAL NETWORK

### *A. Principle of RBF neural network*

RBF neural network is a three-layer feed-forward network [10]: the first layer is the input layer, formed by the signal source node; the second layer is the hidden layer, its unit number depends on the needs of the problem; the third layer is the output layer, responding to the impact of input mode. Its topology is shown in Fig. 1.

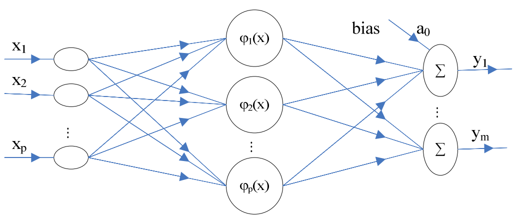


Figure 1. RBF neural network topology

RBF network mapping consists of two parts:

(1) The non-linear transformation from the input space to the hidden layer space.

Select most commonly used Gaussian function as RBF. The output of the *ith* neuron of hidden layer is expressed by the following formula:

$$R_i(r) = \phi(\| r - c_i \|) = \exp\left[ -\frac{(r - c_i)^2}{2\sigma_i^2} \right] \quad (3)$$

Where: $r$ is a input vector, $r = [r_1, r_2]^T$; $c_i$ and $\sigma_i$ were the center and width of RBF; $\phi(\bullet)$ is the base function; $\| \bullet \|$ is the Euclidean norm.

(2) The linear merge from the hidden layer space to the output space.

The output of *ith* neuron of RBF neural network's output layer is as followed:

$$y_i = \sum_{j=1}^{m} \omega_{ij} R_j(r) \quad (4)$$

Where: $p$ is the number of hidden layer nodes; $y_i$ is the ith outputs, here $y = [y_1, y_2]^T$; $\omega_{ij}$ is the connection weight from the *j th* node of hidden layer to the ith node of output layer.

### *B. Network parameters' optimization*

When the issues to be solved are complicated, the design of network structure by artificial means will be more difficult. So the integration of highly efficient automated design methods are required. For RBF neural network, adjustable structure parameters are the center and width of the Gaussian function. Once these two parameters were determined, weights of output layer can be obtained solving linear equations. Therefore, the training of center and width of RBF is an important criterion for the design.

In this paper, PSO algorithm is adopted to identify the parameters center $c$ and width $\sigma$. Parameter identification requires certain criterion. The purpose of neural network training is to find parameters which can reduce error. So, the fitness function of the *ith* individual is designed as followed:

$$f(d) = \sum_{j=1}^{n} e^d = \sum_{j=1}^{n} (y_j - \hat{y}_j)^2 \quad (5)$$

Where, in the *dth* iteration, $y_j$ is the corresponding true fault state value of the *jth* training sample. $\hat{y}_j$ is the corresponding estimates of the *jth* sample. So, when the fitness value is minimum, the estimate error is minimum and the structure is optimal.

Corresponding to each feasible solution, the center $c$ and width $\sigma$ are independent variables of the particle position function. When the fitness value achieves the optimization, corresponding parameters center $c$ and width $\sigma$ of RBF function is also the parameters that make the neural network structure best.

## IV. APPLICATION ON VOLTAGE TRANSFORMER FAULT DIAGNOSIS

Transmission and transformation equipments include a wide range of equipments. Between different devices, the technical complexity and fault mechanisms vary a lot, the status and fault types are also characterized by very different parameters. However, because the fault diagnosis principle is the same, a well performed diagnosis model can be applied on different types of transmission equipment diagnosis as long as appropriate input and output modes are determined. In this paper, voltage transformer is taken for example to design diagnostic model.

### *A. Determination of input and output modes*

DGA is the most convenient and effective means of the current oil-immersed power transformer fault diagnosis. It is effective to found power transformer failure and the potential level of development to prevent major accidents. Therefore, we select dissolved gases as condition parameters. In selection of condition parameters, there are two objectives: keep analysis accuracy but select as few as possible parameters. So, the network model of the DGA data chooses $H_2$, $CH_4$, $C_2H_6$, $C_2H_4$, $C_2H_2$ as input vectors. Voltage faults are generally divided into two types, discharge and over-heated; five kinds of states, normal (O1), High-temperature overheat (O2), Low-temperature overheat (O3), low energy discharge (O4), high-energy discharge (O5). Number of output nodes is equal to the number of fault types. The output vector consists of five output neurons' value. Each neuron only has two type of outputs, 0 or 1. The 5 output results are expressed as, O1: 10000, O2: 01000, O3: 00100, O4: 00010, O5: 00001.

### *B. Data Preprocessing*

As these entered state values of gas vary widely, it is not suitable to input these raw data directly into the model. Otherwise, a series of important features of the network would be difficult to obtain, because the information of some relatively small numbers could not be detected. In order to fully explore the valid information in the original data, this paper adopts fuzzy technology in the data pre-processing of DGA raw data [9]. Select sigmoid function as membership function:

$$y_i = 1/(1+\exp(-x_j / x_{ja})) \qquad (6)$$

Where: $x_i$ is the actual measured value of the *ith* gas; $x_{ia}$ is its attention value; $y_i$ is the corresponding network input. Attention values are shown in Table I.

TABLE I. THE ATTENTION VALUE OF GAS

| **Parameters** | **$H_2$** | **$CH_4$** | **$C_2H_6$** | **$C_2H_4$** | **$C_2H_2$** |
|---|---|---|---|---|---|
| **Attention Value**(μL/L) | 100 | 50 | 100 | 100 | 3 |

### *C. Sample selection*

There are 51 group typical DGA test records and their corresponding results which have been identified are collected. Choose 36 sets of all the data as training samples; the left 15 sets samples as testing samples.

## V. CASE STUDY

The network training and simulation is realized in the MATLAB7.0 platform. In the network training process, the fitness value of particle swarm stabilized with the number of iterations increases. The global optimal solution was found, as well as the corresponding network parameters *c*, σ. As shown in Fig. 2, the curve posed by red * shapes. According to the selected 36 sets training sample data, RBF neural network is trained. The error performance curve is as shown in Fig. 3. It can be clearly seen that RBF network converges very quickly.

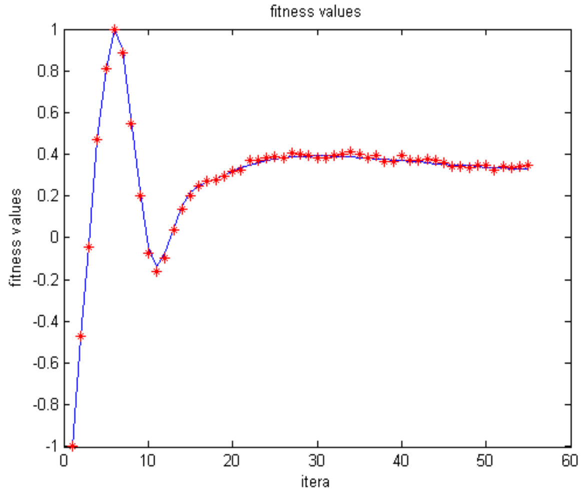


Figure 2. Example of a figure caption. *(figure caption)*

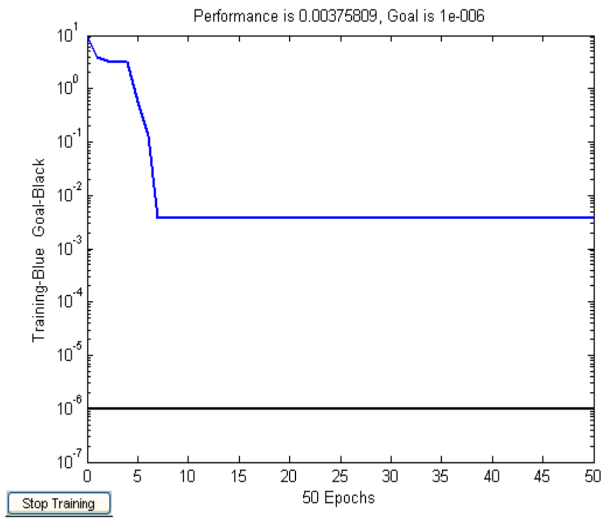


Figure 3. Mse decline curve in training process

For comparison purposes, 3 neural networks were trained, including a BP neural network, a RBF neural network without optimization and a RBF neural network optimized by PSO algorithm. The training results are shown in Table II.

TABLE II. COMPARISON OF TRAINING RESULTS WITH DIFFERENT ALGORITHMS

| Algorithm | Training time/s | Iteration | Mse |
|---|---|---|---|
| BP | 9.96924e-007 | 189 | 1e-006 |
| RBF | 6.18193e-007 | 36 | 2.4071 |
| PSO-RBF | 0.00375809 | 7 | 4.7863E-05 |

After the networks were established, 15 test samples were used to test the fault diagnosis performances of each network. Results are shown in Table III.

TABLE III. TABLE TYPE STYLES

| Algorithm | Testing sample number | Correct number | Fault-tolerant rate/% |
|---|---|---|---|
| BP | 15 | 5 | 33.3333 |
| RBF | 15 | 7 | 46.6667 |
| PSO-RBF | 15 | 11 | 73.3333 |

By analyzing the result data of network training and fault identification, it is found that:

(1) From the training time and error terms of view: although BP algorithm (not stable, the error performance of each training varies widely, the table shows the more general case)trained for a longer time and iterates a few more steps, its total average error variance achieve the expected value of 1e-006; RBF network iterated 36 times to reach stability with the fastest training velocity, but because of the small sample size, it did not achieve the desired error; PSO-RBF iterated only 7 times to achieve a smaller margin of error, but because of lots of operational links, the training time is slightly longer.

(2) From the fault identification performance of view: BP algorithm only correctly identified 5 testing samples, it's the least number of all, and therefore it has lowest rate of fault-tolerant. This can be explained by the feature that BP network has a high demand for sample size; RBF identified correctly a bit more samples, fault-tolerant rate is 46.67%; after the effective PSO optimization, PSO-RBF fault-tolerant rate increased by 57.14% on the basis of RBF network.

(3)Examples proved that PSO-RBF neural network needs fewer steps to be trained and has a better error performance and a higher fault tolerance rate. It is proved that the attempt to optimize the RBF neural network by PSO algorithm in this paper is successful.

## VI. CONCLUSION

Through the discussions and empirical analysis above, the following conclusions can be drawn:

(1)This research integrated PSO algorithm and RBF neural network. Optimized by intelligent and concise PSO algorithm, the improved network not only has better generalization and mapping capabilities, but also has higher convergence speed and better learning ability. It is embodied in the diagnosis case.

(2) When the method was used in transformer fault diagnosis, the network demonstrated good identification ability. In spite of small number of training samples, the fault tolerant rate was increased by 57.14% compared with the single RBF neural network. It can be expected that if the number of samples is sufficient, diagnosis effects would be even better.

(3) Subject to conditions, the network model was merely used in voltage transformer DGA fault diagnosis. However, it can be also applied on the fault diagnosis of other transmission equipments as long as sufficient samples could be obtained and the appropriate input, output modes are determined. It's no doubt that the model possesses practical value in engineering practice.

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