Application of Wavelet Neural Network with Particle Swarm Optimization Algorithm in Boiler Faults Diagnosis

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Abstract. In view of the main fault type in boiler steam water system, a variety of complex fault data are extracted. A wavelet neural network fault diagnosis based on particle swarm optimization algorithm is designed. The wavelet neural network constructed by three-layer wavelet neural network, is trained by particle swarm algorithm. By optimizing the weights factor, scale factor and shift factor wavelet neural network on particle swarm algorithm, the training speed of wavelet neural network is accelerated and the training accuracy is also improved. The simulation results show that the improved wavelet neural network algorithm is applied to the fault diagnosis of boiler, which can effectively eliminate the influence of redundant connection structure on network diagnostic ability and provide a new way for the boiler fault diagnosis.

Introduction

Among the traditional fault diagnosis methods, the main methods are through monitoring the feed water flow rate and the outlet temperature of the super-heater to diagnose the fault type. But when the fault occurs, due to the high coupling between operation parameters, a large number of parameters changes are usually appeared. It is very difficult to find the fault location and troubleshooting. So it is necessary to introduce intelligent technology help operators for boiler real-time monitoring, fault diagnosis and operational guidance. The rapid development of neural network provides a new approach for boiler fault intelligent diagnosis technology that can solve many difficult practical production problems [2]. Currently, the popular wavelet neural network is one of them. The traditional wavelet neural network adopts error back propagation algorithm(BP), prone to fall into local optimal point, slow convergence and sample dependency problems. Regarding the issue above, in this paper, in order to enhance the global search ability and optimize the parameters of wavelet neural network, particle swarm optimization is applied to the fault diagnosis of power boiler steam water and has achieved a good effect of diagnosis [3].

Wavelet Neural Network

Wavelet neural network(WNN) is combined with wavelet theory and artificial neural network. According to the needs of fault diagnosis in boiler system, the mother of wavelet base-Morlet is used as the activation function in the traditional neural network. Its structure is shown in figure 1. $X_1, X_2, \cdots, X_K$ are used as input characteristic parameters of Wavelet neural network. $Y_1, Y_2, \cdots, Y_m$ are adopted as output of Wavelet neural network. w_{ij} and w_{jk} are used as wavelet neural network weights. a_j and b_j are used as the wavelet scale translation parameters. The network adopts cosine modulated gaussian wave, whose time and frequency domain has high resolution. It is suitable for complex the boiler fault diagnosis. $h(j)$ is adopted as wavelet basis function formula

$$h(j) = \cos\left[1.75\left(\mathrm{x} - b\right)/a\right] e^{-x^2/2} \quad (1)$$

A training sample is $X = \left[X_1, X_2, \cdots, X_p\right]$ .The actual output sample is $Y = \left[\mathrm{y}_1, \mathrm{y}_2 \cdots \mathrm{y}_\mathrm{q}\right]$ .The desired output is $T=[t_1,t_2\cdots t_q]$. The number of hidden layer nodes is L. The size of input sample is N. The network approximation error is E. That is :

$$E=\frac{1}{N}\sum_{n=1}^{N}\sum_{\mathrm{k}=1}^{\mathrm{q}}\left(\mathrm{t_k}-\mathrm{y_k}\right)^2 \tag{2}$$

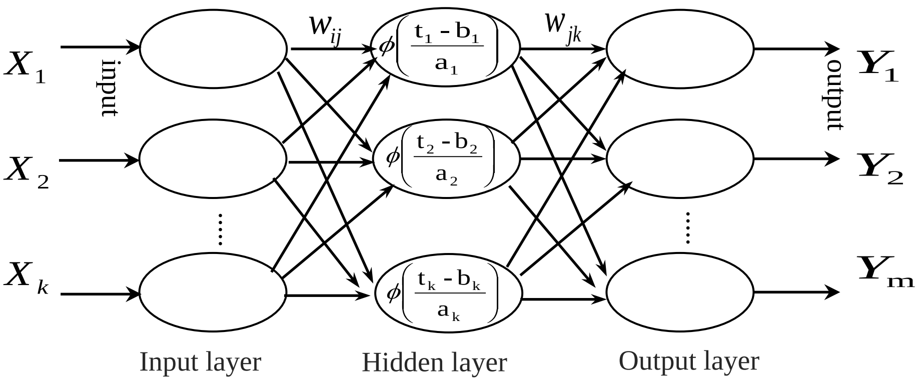

Fig.1 Three layers structure of wavelet neural network

The actual output of the wavelet neural network is calculated as

$$\mathrm{y}=\sum_{i=1}^{L}w_{ik}\cos\left[1.75\left(\sum_{i=1}^{k}w_{ij}x_i-b_j\right)\Big/a_j\right]e^{-x^2/2} \tag{3}$$

Based on the formula (3), the construction of high performance of the Wavelet neural network is connected with its weights, scaling and proper translation factor values. And whether the selection of these parameters is proper or not rely on the optimization of Wavelet neural network's training algorithm. Thus it is important to find a suitable wavelet neural network algorithm [4].

The Particle Swarm Optimization Application on wavelet neural network

Particle swarm optimization algorithm(PSO) is initialized to a group of random particles (random solution) in the solution space, and then find the optimal solution by iteration. Each particle represents a potential optimal solution of the extremal optimization problem. Particle's characteristics are represented by the position, speed and fitness.The degree of fitness value is used as a standard of evaluating the particles. In each iteration, the particles is updated by tracking two "extreme". One is optimal solution which is found by the particles themselves, called individual extreme value-Pbest. The other extreme value is optimal solution which is found in the entire population. It is global extreme value-Gbest. Assuming a D-dimensional searching space, there is a population composed of the N particles $X=\left(X_1,X_2,\cdots,X_\mathrm{n}\right)$. Among them, i particle is represented as a D-dimensional vector $X_i=\left[X_{\mathrm{i}1},X_{i2},\cdots,X_{iD}\right]^T$. It's not only on behalf of the position of the i particle in D-dimensional space, but represents a potential solution of the problem. Based on the objective function, it's easy to calculate the fitness value of particles. The i particle velocity is $V_\mathrm{i}=\left[V_{\mathrm{i1}},V_{\mathrm{i2}},\cdots,V_{\mathrm{iD}}\right]$. Its Pbest is $P_\mathrm{i}=\left[P_{\mathrm{i1}},P_{\mathrm{i2}},\cdots,P_{iD}\right]$. Its Gbest is $P_g=\left[P_{g1},P_{g2},\ldots,P_{gD}\right]$. In each iteration, the particles updating their own speed and position by individual and global extreme value. The updated formula is

$$V_{id}^{k+1}=\omega V_{id}^{k}+c_1r_1\left(P_{id}^{k}-X_{id}^{k}\right)+c_2r_2\left(P_{gd}^{k}-X_{id}^{k}\right) \tag{4}$$

$$X_{id}^{k+1}=X_{id}^{k}+V_{id}^{k+1} \tag{5}$$

In the above formula, ω is the inertia weight; $d=1,2,\cdots,D$; $i=1,2,\cdots,n$; k is the current iteration number; V_{id} is particle velocity; c_1 and c_2 are non-negative constant, which is called acceleration factor; r_1 and r_2 are random number for the division between the zero and one. To prevent blind search, the general position and its speed is limited to a certain range $[-X_{i\max}, X_{i\max}]$and$[-V_{\max}, V_{\max}]$.When the three layers of Wavelet neural network constructed in this paper adopts the PSO to optimize, the node number of input layer, hidden layer and output layer of Wavelet neural network is set 9, 10 and 4, and output layer parameter is set into 4×1 dimensional matrix. When it has its corresponding problem, display an element 1, otherwise 0. The random distribution function generates the initial particle velocity. Adjustment of the parameters is composed of each layer weights and scale factor and shift factor of hidden layer unit in wavelet basis function. So the basic PSO is used to realize the training of weight parameters.Assume n_i, n_h an n_o represent the number of input layer, hidden layer and output layer neurons calculated by the PSO. Each dimension of particle size D can be expressed as:

$$D = n_i \times n_h + n_h \times n_o + 2n_h \tag{6}$$

According to formula (6), Wavelet neural network's weights and scale factor and shift factor of the hidden layer unit in wavelet basis function are arranged in order. Particles are formed by vectors $X_i = \left[\omega_{11}^1, \omega_{12}^1, \cdots, \omega_{n_i n_h}^1, \omega_{11}^2, \omega_{12}^2, \cdots, \omega_{n_h n_o}^2, a_1, \cdots, a_h, b_1, \cdots, b_h\right]^T$ .Each particle weight is assigned into the neural network, and then enter all training samples, calculate the mean square error between the neural network output and the desired output as particles fitness. The fitness function is

$$F = \frac{1}{N}\sum_{n=1}^{N}\sum_{\mathrm{j}=1}^{\mathrm{q}}\left(\mathrm{t_{ij}} - \mathrm{y_{ij}}\right)^2 \tag{7}$$

In the formula, N is the total number of samples for the training; y_{ij} is actual output for the network; t_{ij} is the desired output of the network. The terminating conditions are selected as the maximum number of iterations. Finally acquired X_i . It symbolizes the approximate solution of the global optimal solution.The basic process algorithm is as follows:

Step 1: Determine the size of the particle swarm. Initialize related parameters of the PSO algorithm. Set the learning factor, the maximum allowable number of iterations and the target error.

Step 2: On the basis of the targets, the fitness value of particles can be calculate. Based on the initial fitness value of particles, groups extreme value and individual extreme value can be found.

Step 3: According to the formula (4) and (5), particle position and velocity is updated .

Step 4: Based on whether fitness of new particles is better than individuals and groups extreme value or not, decide whether individuals and groups extreme value is set to the new location.

Step 5: Verify whether reach the termination condition. When the number of iterations reaches the maximum number of times or the minimum requirements for a given error, stop the iteration and output the global optimal position; otherwise, return to the step 3 to continue the searching [5].

Simulation Experiment

Based on the literature [6], when superheater leakage occurs, the main steam flow rate increases before the break point, causing working medium temperature in the superheater has dropped. The working medium temperature will be reduced after the break point, leading to outlet temperature will rise significantly. Deviation is far from normal temperature. On the basis of the above, fault data samples of boiler are extracted; the 9 data of characteristic parameters are chosen, as is shown in the table 1. So the input node is 9. At the same time, choose four kinds of single fault as output, such as different location of the superheater, economizer leakage and so on. The output node is 4, as is shown in the table 1. Data in the table refer to 350MW Thermal Power Plant Boiler Unit fault simulation system parameters. After finishing the sample data, the data are normalized. Under the condition of sample feature attribute is complicated , it can make use of principal component analysis, or some method of rough set dimension to reduce feature attributes. Each fault selection is chosen 300 groups data, a total of 1200 sets of data and in random order. The 1200 experiment groups data are divided into training data and testing data. Based on experience, 1000 group is selected as the training data and 200 groups is selected as test data.

According to the empirical formula $l = \sqrt{(x+y)} + c \ \left(c \in [0,10]\right)$, (8) the number of best implied network hidden layer node range from 4 to 13. Through changing the number of hidden layer nodes by trial and error method and comparing network convergence performance, determine the optimal number of hidden layer nodes [7]. 100 sets of sample data form single fault type are selected. Among them, 5 sets of data are used for network test, and the training times are set to 100 times. The trends between the number of hidden layer nodes and the error rate are as Table 1.

Table 1. Original sample data

Sample	1	2	3	4
Water supply [t/h]	1348	1351	1355	1347
Furnace pressure [KPa]	0.155	0.136	0.173	-0.105
Outlet temperature of platen superheater [℃	516	549	517	552
Inlet temperature of platen superheater [℃	560	550	517	550
Outlet temperature of high temperature superheater [℃]	575	577	576	580
Outlet pressure of high temperature superheater [MPa]	24.80	24.75	24.79	24.82
Outlet temperature of low temperature superheater [℃]	430	472	427	475
Outlet temperature of reheater [℃]	577	571	575	573
Inlet temperature of reheater [℃]	491	492	493	497

Based on the Fig.2, with the increase of the number of hidden layer nodes, error rate has the trend of first decreases after increases. It can be found when the test sample error rate is minimal, hidden layer nodes is 10. So the node hidden layer 10 is selected as the best network node.

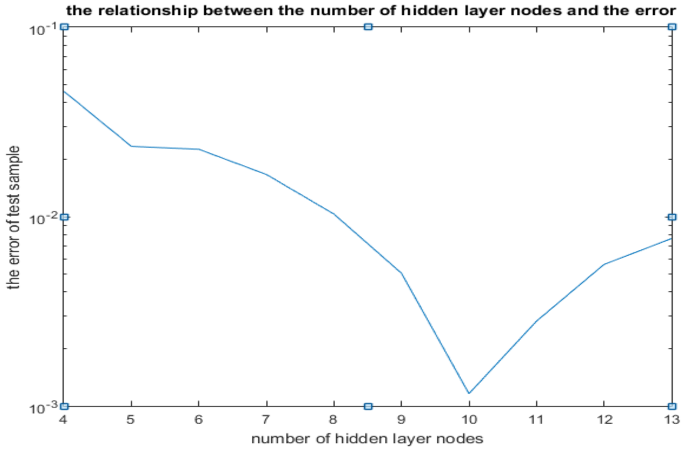

Fig.2 The network test error of different hidden layer

After determining the input, output and hidden layer nodes, fault training samples are input and the number of particles is initialized to 20. The experiment adopts the maximum number of the evolution-1000 times as the termination conditions. The algorithm test is composed by the traditional neural network and Wavelet neural network which is optimized with BP algorithm. With the help of the training of the application of particle swarm optimization on wavelet neural network (PSO-WNN), the best obtained training error curve is shown in the following Fig.3.

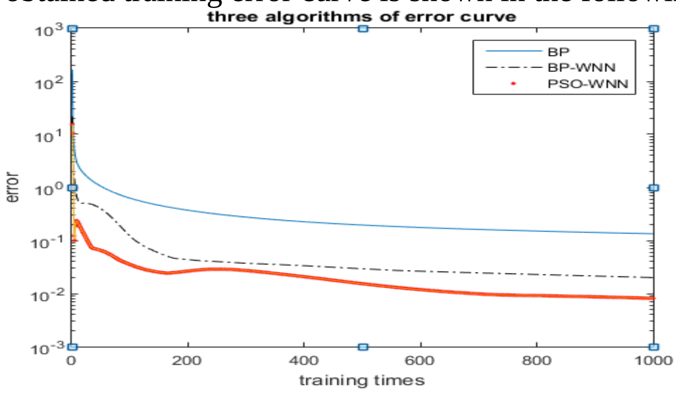

Fig.3 The comparison of three algorithms of error curve

The figure shows that there is an obvious difference in terms of BP, WNN, PSO-WNN in error accuracy and convergence time of boiler fault diagnosis. Traditional BP algorithm achieves rapid convergence before the number of training is up to the step 200, but after 200 steps the rapid is slow leading to the stagnation of error curve. Before the step 200, BP-WNN algorithm is greater than the traditional BP algorithm in the magnitude of convergence and accuracy. After 200 steps, Wavelet neural network’s limitations which is inherited from BP algorithm begin to appear. No matter in the unit number of training precision on the convergence rate and the error precision, Wavelet neural network based on PSO algorithm is more excellent than the above two algorithms. Through analysis and comparison, compared with the expected output, the error of BP diagnosis is bigger, and the error of PSO-WNN algorithm is minimum. It is shown that using PSO-WNN algorithm is closer to the desired output value and has a high precision, which can greatly improve the efficiency and capacity of the network convergence. After the training is completed, the 200 groups of test data which are used as the test sample are input into neural network test. The result can correctly identify the boiler failure. Compared prediction output with the actual type of failure through the network, fault diagnostic capabilities can be predicted.The results of diagnostic algorithms are shown in Table.2.

Table.2 The comparison of the results of three algorithms

Test sample	Ideal output	Algorithm	Diagnosis				Fault types
			O_1	O_2	O_3	O_4	
1	1000	BP	0.8949	0.0097	0.0009	0.0010	Leakage of platen super heater
	1000	BP-WNN	0.9982	0.0065	0.0009	0.0007	
	1000	PSO-WNN	1.0005	0.0007	0.0007	-0.0006	
2	0100	BP	0.0028	0.9891	0.0027	0.0080	Leakage of low temperature super heater
	0100	BP-WNN	0.0024	1.0002	0.0005	0.0040	
	0100	PSO-WNN	0.0005	1.0004	0.0001	-0.0015	
3	0010	BP	0.0028	0.0046	0.9984	0.0032	Leakage of high temperature super heater
	0010	BP-WNN	0.0023	0.0007	0.9987	0.0027	
	0010	PSO-WNN	0.0001	0.0006	0.9992	-0.0009	
4	0001	BP	0.0030	0.0029	0.0017	0.9984	Economizer leakage
	0001	BP-WNN	0.0013	0.0023	0.0008	1.0004	
	0001	PSO-WNN	0.0009	-0.0004	0.0001	1.0017	

As can be seen from table 2, using PSO trained wavelet network can accurately diagnose the fault of super heater leakage and another three faults. Besides, it can still draw a more accurate diagnosis on the failure data which is not trained. It is indicated that compared with the traditional BP neural network and Wavelet neural network, the design of new network has a strong generalization ability.

Conclusion

Aimed at the requirement of boiler fault diagnosis is convenient, quick, and accurate, the wavelet neural network method based on particle swarm optimization algorithm is proposed. This method can not only overcome the disadvantages of the BP algorithm, such as making the neural network fall into local minimum, slow convergence and so on, but has greatly improved in terms of speed and recognition accuracy. It can classify the boiler common type of fault. It has the ability to eliminate the influence of redundant connection structure on network diagnostic capacity. In the case of a large number of training samples, this method can also get a better diagnostic results.

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