Sensors & Transducers, Vol. 169, Issue 4, April 2014, pp. 101-106

Sensors & Transducers

http://www.sensorsportal.com

Fault Diagnosis of Hydraulic Servo Valve Based on Genetic Optimization RBF-BP Neural Network

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Received: 13 February 2014 /Accepted: 7 April 2014 /Published: 30 April 2014

Abstract: Electro-hydraulic servo valves are core components of the hydraulic servo system of rolling mills. It is necessary to adopt an effective fault diagnosis method to keep the hydraulic servo valve in a good work state. In this paper, RBF and BP neural network are integrated effectively to build a double hidden layers RBF-BP neural network for fault diagnosis. In the process of training the neural network, genetic algorithm (GA) is used to initialize and optimize the connection weights and thresholds of the network. Several typical fault states are detected by the constructed GA-optimized fault diagnosis scheme. Simulation results shown that the proposed fault diagnosis scheme can give satisfactory effect. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Fault diagnosis, RBF-BP neural network, Genetic algorithm, Servo valve.

1. Introduction

Electro-hydraulic servo valve plays a pivotal role in the hydraulic servo system of rolling mills. It has some advantages such as high control precision and fast response. However, due to the complexity of its components and the high precision, together with the fact that it usually works in the environment of high temperature and high pressure, so the failure frequency is higher. Once a failure occurs, huge economic losses will be caused. Therefore, the effective fault diagnosis and maintenance of hydraulic servo valve has important practical significance [1-3].

The task of fault diagnosis consists of the determination of the type of fault with as many details as possible such as the fault size, location and time of detection [4]. Due to the broad scope of the process fault diagnosis problem and the difficulties in its real time solution, various computer aided approaches have been developed over the years [5]. Artificial intelligence techniques, such as expert systems, artificial neural networks (ANN), fuzzy logic systems, and genetic algorithms etc. have been employed to assist the diagnosis [6].

Back-propagation (BP) neural network can approximate any nonlinear function arbitrary precision, and its self-learning and adaptive ability is good. But a major criticism is common moved against BP algorithm [7]. BP algorithm is actually a gradient method and therefore there is no guarantee at all that the global minimum of error surface can be reached. Radial Basis Function (RBF) neural network is a combination of Learning Vector Quantization (LVQ) and gradient descent. Since the RBFNN has a faster training procedure substantially and adopts typical two-stage training scheme, it can avoid solution to fall into local optima [8]. 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 [9]. Designing an optimal ANN structure and its parameters to maximize the classification accuracy is still a crucial and challenging task [10]. In contrast, a RBF-BP combination will perform fault detection based on both current measurements and future predication, which would be produce more reliable results [11]. So this article combines two single networks together to constitute a RBF-BP neural network. The neural network structure and the selection of initial connection weights and thresholds have much influence on network training, but they usually cannot be obtained accurately. Genetic algorithm (GA) has strong robustness and the ability to search the global optimal solution [12, 13]. So, genetic algorithm is introduced in this paper to optimize the neural network for getting the best initial weights and thresholds, thereby enabling the network has a faster convergence speed, higher stability, and also avoiding the problem of local minimum.

2. Material and Methods

2.1. Construction of a RBF-BP NN

An appropriate RBF-BP neural network is needed to construct first. RBF-BP neural network is a double-hidden-layer neural network made up of combination of a RBF subnet and a BP subnet, using a Gaussian function as transfer function in the first hidden layer node and an S-type function as transfer function in the second one. RBF neuron model is shown in Fig. 1.

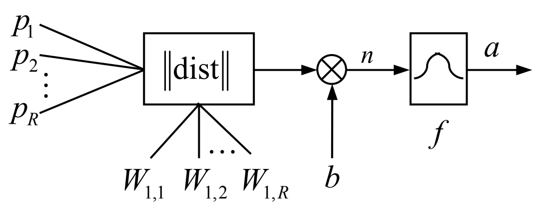

Fig. 1. RBF neuron model.

The output expression of radial basis function is

$$a = f\left(\|\boldsymbol{W} - \boldsymbol{P}\| \cdot b\right) = \text{radbas}\left(\|\boldsymbol{W} - \boldsymbol{P}\| \cdot b\right), \quad (1)$$

where ‘radbas’ denotes radial basis function, and it is usually a Gaussian function, which can be expressed as:

$$a(n) = \text{radbas}(n) = e^{-n^2}, \quad (2)$$

and

$$\begin{aligned}\|\boldsymbol{W} - \boldsymbol{P}\| &= \sqrt{\sum_{i=1}^{R}\left(w_{1,i} - p_i\right)^2} \\ &= \left[\left(\boldsymbol{W} - \boldsymbol{P}^{\mathrm{T}}\right)\left(\boldsymbol{W} - \boldsymbol{P}^{\mathrm{T}}\right)^{\mathrm{T}}\right]^{1/2}\end{aligned}, \quad (3)$$

where $\boldsymbol{W}$=[$w_{1,1}$, $w_{1,2}$,…$w_{1,R}$] is the weighted vector, $\boldsymbol{P}$=[p_1, p_2,…p_R]$^{\mathrm{T}}$ is the input vector.

BP neuron model is shown in Fig. 2.

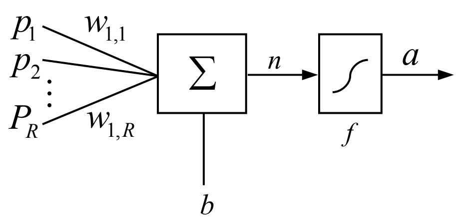

Fig. 2. BP neuron model.

If the transfer function is chosen as a hyperbolic tangent function, the output expression of BP neuron is:

$$a = f(\boldsymbol{Wp} + b) = \tan\text{sig}(\boldsymbol{Wp} + b), \quad (4)$$

and it can be rewritten as

$$a(n) = \text{tansig}(n) = \frac{1 - e^{-n}}{1 + e^{-n}}, \quad (5)$$

If the transfer function is chosen as a Log-Sigmoid S-type function, the output expression of BP neuron is:

$$a = f(\boldsymbol{Wp} + b) = \log\text{sig}(\boldsymbol{Wp} + b), \quad (6)$$

The above equation can be expressed as:

$$a(n) = \text{logsig}(n) = \frac{1}{1 + e^{-n}}, \quad (7)$$

The structure of RBF-BP neural network is shown in Fig. 3, where $w_{1,j(i)}$ is the weight of p_i corresponding to the j-th neuron in the first hidden layer, $(b_{11},....b_{1j})^{\mathrm{T}}$ is the threshold vector of the first hidden layer; $w_{2,n(j)}$ is the weight of the j-th neuron in the first hidden layer corresponds to the n-th neuron in the second hidden layer, $(b_{21},....b_{2n})^{\mathrm{T}}$ is the threshold vector of the second hidden layer; $w_{3,k(n)}$ is the weight of the n-th neuron in the second hidden layer corresponds to the k-th neuron in the output layer, $(b_{31},....b_{3k})^{\mathrm{T}}$ is threshold vector of the output layer, and $\boldsymbol{Y}$=(y_1, y_2, ...y_k)$^{\mathrm{T}}$ is the output vector.

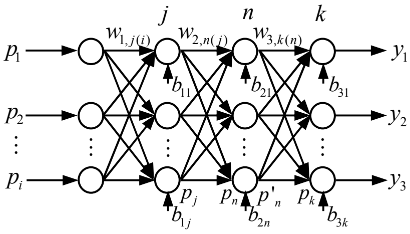

Fig. 3. RBF-BP neural network.

2.2. Algorithm Description

Delta rule is used as the learning rule of ANN in this paper. This rule is a variation of Hebb's rule and based on the simple idea of continuously modifying the weights of the input connections to reduce the difference (the delta) between the desired output and the actual output of the network. It changes the weights in such a way that minimizes the mean square error (MSE) of the network. The mean square error which is used as the evaluating indicator can be described as:

$$\mathrm{MSE} = \frac{1}{m}\sum_{k=1}^{m}\left(y_k - r_k\right)^2 = e\,, \tag{8}$$

where, r_k represents the desired output, y_k denotes the actual output, and m is the number of neurons in the output layer.

Learning process of RBF-BP neural network is divided into two stages: The first stage is forward-propagation. Learning samples from the input layer are processed by the hidden layer, calculated each neuron output backward from the first layer of the network, and then transmitted to the output layer. The second stage is back-propagation. The error signal is calculated reversely by connecting path, the effect of each weight and threshold on total deviation is calculated forward from the last layer, and the weights and thresholds of the network are revised continuously.

In the process of forward-propagation, the output p_j of the j-th neuron in the first hidden layer is excited by radial basis function. According to equation (1), (2) and (3), it can be derived as

$$p_j = \exp\left(-b_{1j}^2 \cdot \sum_{i=1}^{l}\left(w_{1,j(i)} - p_i\right)^2\right), \tag{9}$$

where l is the number of neurons in the input layer.

The input of the n-th neuron in the second hidden layer is the sum of weighted and threshold value of all neurons in first hidden layer, which can be described as

$$p_n = \sum_{j=1}^{r} w_{2,n(j)} \cdot p_j + b_{2n}\,, \tag{10}$$

where r is the number of neurons in the first hidden layer. According to equation (4) and (5), the output of the n-th neuron in the second hidden layer can be described as

$$p_n^{'} = \mathrm{tansig}\left(p_n\right) = \frac{1 - e^{-p_n}}{1 + e^{-p_n}}\,, \tag{11}$$

The k-th input of output layer neurons is the sum of weighted and threshold value of all neurons in second hidden layer, that is

$$p_k = \sum_{n=1}^{s} w_{3,k(n)} \cdot p_n^{'} + b_{3k}\,, \tag{12}$$

where s is the number of neurons in the second hidden layer. According to equation (6) and (7), the output of k-th neuron in the output layer can be gained as

$$y_k = \mathrm{logsig}\left(p_k\right) = \frac{1}{1 + e^{-p_k}}\,, \tag{13}$$

The error of the k-th output y_k corresponding to its ideal output r_k is

$$e_k = r_k - y_k\,, \tag{14}$$

According to equation (8), the error performance index of the p-th sample can be derived as

$$e_p = \frac{1}{m}\sum_{k=1}^{m} e_k^2\,, \tag{15}$$

In the process of back propagation, the scaled conjugate gradient (SCG) algorithm is used to adjust the weights and thresholds between layers [14]. SCG belongs to the class of Conjugate Gradient Methods, which show superlinear convergence on most problems. By using a step size scaling mechanism, SCG avoids a time consuming line-search per learning iteration, which makes the algorithm faster than other second order algorithms. The first iteration searches along the descent direction of steepest gradient [15], that is

$$\boldsymbol{q}_0 = -\boldsymbol{g}_0\,, \tag{16}$$

Then linear search which decides the best distance is carried out along the current search direction:

$$\boldsymbol{x}_{h+1} = \boldsymbol{x}_h + \alpha_h \boldsymbol{q}_h\,, \tag{17}$$

$$\boldsymbol{q}_h = -\boldsymbol{g}_h + \beta_h \boldsymbol{q}_{h-1}\,, \tag{18}$$

where $\boldsymbol{q}_h$ denotes the search direction of the h+1 iteration, which is decided by the iteration gradient and search direction of the h-th iteration; $\boldsymbol{g}_h$ denotes the gradient vector at the h-th iteration; $\boldsymbol{x}_h$ is the threshold vector between layers in the h-th iteration; β_h is the coefficient which can be calculated by:

$$\beta_h = \frac{\boldsymbol{g}_{h+1}\left[\boldsymbol{g}_{h+1} - \boldsymbol{g}_h\right]}{-\boldsymbol{q}_h^{\mathrm{T}}\boldsymbol{g}_h}, \quad (19)$$

α_h in equation (17) is the step length, which can be given by:

$$\alpha_h = \frac{\mu_h}{\delta_h} = \frac{\mu_k}{\boldsymbol{q}_h^{\mathrm{T}} s_h + \lambda_h \left|\boldsymbol{q}_h\right|^2}, \quad (1)$$

where

$$\mu_h = -\boldsymbol{q}_h^{\mathrm{T}}\boldsymbol{g}_h,\ \delta_h = \boldsymbol{q}_h^{\mathrm{T}} s_h$$

$$s_h = \frac{e'(\boldsymbol{x}_h + \sigma_h \boldsymbol{q}_h) - e'(\boldsymbol{x}_h)}{\sigma_h} + \lambda_h \boldsymbol{q}_h,\ 0 < \sigma_h \le 1.$$

The value of σ_h should be as small as possible. When σ_h is small enough ($\sigma_h \le 10^{-4}$), the value of σ_h is not critical for the performance of SCG. Because of that, SCG seems not to include any user dependent parameters which values are crucial for the success of the algorithm. This is a major advantage compared to the line search based algorithms which include those kinds of parameters.

In the process of training the neural network, genetic algorithm is used to initialize and optimize the connection weights and thresholds of the network. Optimization neural network with genetic algorithm mainly includes:

1) Population Initialization.

The main success of genetic algorithm depends mainly upon the individuals chosen in the initial population and the size of population. The initialization of population is the most basic steps of genetic algorithm. The population is initialized using the binary code.

2) Fitness Function.

The fitness function is transformed by the objective function, and the individual pros and cons are compared through the fitness.

3) Choice.

Choice is used to determine the recombination or crossover individual, as well as how many offspring individuals will be produced by the selected individual. The parent individual is chosen in accordance with the above fitness.

4) Cross.

Cross is the gene recombination. Genetic recombination is to generate a new individual by combining from parent mating population information.

5) Mutation.

Mutation Variation for offspring after crossing is actually a variation created by progeny gene in the small probability disturbance.

Genetic algorithm gives the mean square error of the output of the neural network by calculating all the samples, and then determines the fitness of every individual. After several generations of calculation, the neural network will evolve to a global minimum, and the error function is as follows:

$$E = \sum_{p=1}^{N} e_p, \quad (21)$$

where N is the number of samples.

2.3. Fault Diagnosis with GA Optimized NN

Electro-hydraulic servo valve is an important component in the hydraulic servo system. Type of its failure is diversity. The typical faults can be divided into fixed orifice clogging, spool stuck or blocked, edge wear of main valve control window, dilapidation of the main valve cover seal, sensor failure, servo amplifier failures, coil failure and so on.

This article uses a RBF-BP neural network for fault diagnosis. First the network structure must be determined and a rational input-output mode must be designed. The experimental data of the following five states of are measured respectively at the pressure of 3 MPa, 3.5 MPa, 4 MPa and 4.5 MPa, 5 MPa, so the output of the network is expressed as the following form:

$Y=(y_1, y_2, y_3, y_4, y_5)$

Normal state: (1, 0, 0, 0, 0)

End limit on spool: (0, 1, 0, 0, 0)

Fixed orifice clogging in one side: (0, 0, 1, 0, 0)

Spool wear: (0, 0, 0, 1, 0)

Zero position misalignment of servo valve: (0, 0, 0, 0, 1)

So the network of this paper consists of 32 inputs, 5 outputs and two hidden layers. The number of neurons in hidden layer and the number of neurons in the input layer has an approximate relation. According to this, the neuron number of the two hidden layers is set at 65. Simulation tests are carried out in the MTALAB platform. Function 'newff' is called to create a BP neural network with double hidden layer. Transfer function for the first hidden layer neuron is set to Gauss-type function 'radbas', and the transfer function for the second hidden layer and the output layer neuron is set to sigmoid-type function of 'tansig' and 'logsig' respectively. 'trainscg' is chosen as the training function, and the learning rate, training times and other relevant parameters are set.

In this paper, genetic algorithm is used to optimize the network weights and thresholds to get the best initial weights and thresholds. In population initialization, each individual is a binary encoded string connected by the weights of input layer - hidden layer 1, thresholds of hidden layer 2, connection weights of hidden layer 1- hidden layer 2, thresholds of hidden layer 2, the connection weights of output layer- hidden layer 2, and thresholds of output layer. The size of the population affects the end result of genetic optimization and the execution efficiency of genetic algorithm, the common population size is 20 to 160. In this paper, the population size is set to 40. The fitness function 'ranking' is chosen for the fitness assignment. Using the stochastic universal sampling (sus) for individual choice. The Crossover probability is set at 0.7, and the most simple single-point crossover is chosen for crossover operator. The mutation probability is set at 0.01.

3. Results and Discussion

Fig. 4 shows the error evolution curve of weights and threshold matrix obtained after genetic optimization. The minimum error e = 0.03942. Fig. 5 is the training error curve of using random weights and threshold (before optimization), Fig. 6 is the training error curve of weights and thresholds of optimized RBF-BP neural network, Fig. 7 is the training error curve of weights and thresholds of double hidden layer BP neural network. The compared data of output prediction, prediction error and training error between several different NN for detecting five different faults are shown in Table 1.

It can be seen by comparison that, although the double hidden layer BP NN and RBF-BP NN can detect the faults occur in electro-hydraulic servo valve, but the test sample errors and the training sample errors of the first two networks are large. While if we use the genetic algorithm to optimize the initial weights and thresholds of NN, the test sample error drops down to 0.03942, and the training sample error decreases to 0.092986. GA makes the training and sample test results of the neural network improve greatly, and this gives better diagnosis results.

4. Conclusion

With the help of genetic algorithm, the weights and thresholds of the neural network can be optimized, and thus, the GA optimized RBF-BP neural network can be used for effective fault diagnosis. Genetic optimization RBF-BP neural network is very useful for fault diagnosis on hydraulic servo valve.

Acknowledgements

This work was supported by the National Key Technology Research and Development Program of China under Grant 2012BAF09B01.

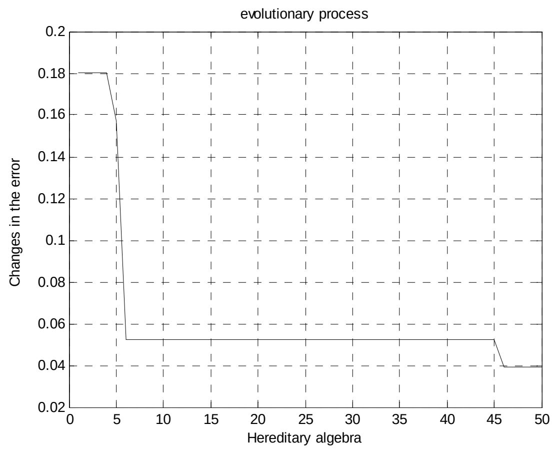

Fig. 4. Error evolution curve.

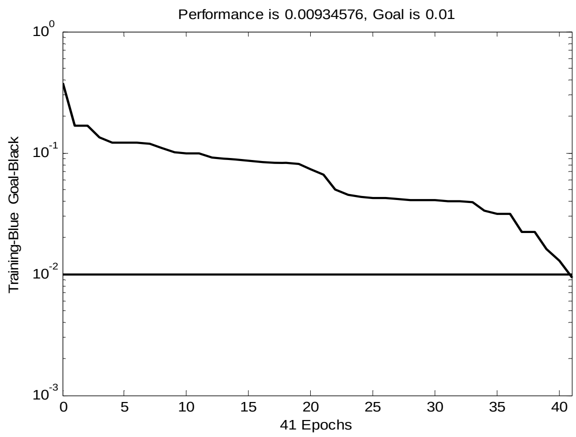

Fig. 5. Training error with random weights.

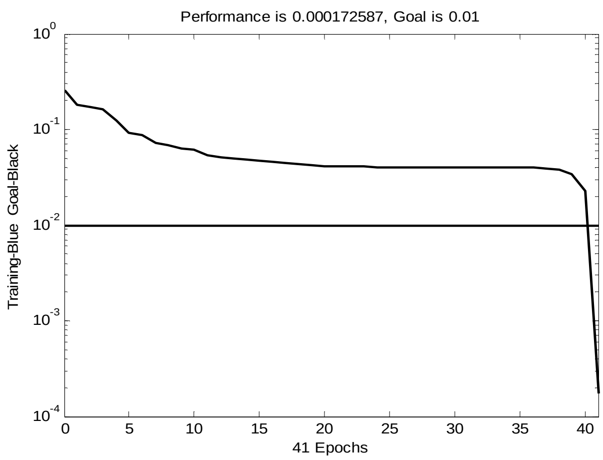

Fig. 6. Training error with optimized RBF-BP.

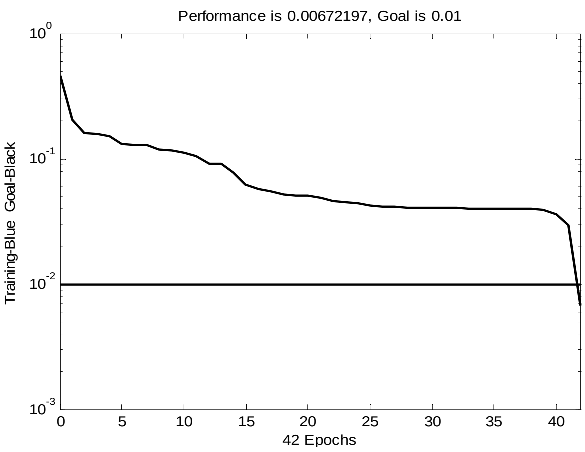

Fig. 7. Training error with double hidden layer BP.

Table 1. Prediction error and training error.

NN model	Iterations	Prediction of test sample: *Y*					Fault type	Error of test sample	Error of training sample
		y_1	y_2	y_3	y_4	y_5			
BP	42	0.8103	0.0249	0.0095	0.0565	0.0094	Normal	0.45389	0.81829
		0.0186	0.9527	0.0515	0.0071	0.0102	End limit on spool		
		0.0025	0.0444	0.9641	0.0032	0.0102	One-side fixed orifice clogging		
		0.4062	0.0129	0.0062	0.9531	0.0202	Spool wear		
		0.0082	0.0200	0.0023	0.0851	0.9646	Zero position misalignment		
RBF-BP	41	0.9897	0.0046	0.2855	0.0039	0.0044	Normal	0.39163	0.62551
		0.0029	0.9907	0.0026	0.0055	0.0113	End limit on spool		
		0.0520	0.0003	0.7379	0.0330	0.0364	One-side fixed orifice clogging		
		0.0053	0.0040	0.0150	0.9961	0.0954	Spool wear		
		0.0062	0.0089	0.0154	0.0075	0.9116	Zero position misalignment		
GA-RBF-BP	41	0.9799	0.0051	0.0006	0.0000	0.0000	Normal	0.03942	0.092986
		0.0002	0.9613	0.0002	0.0027	0.0007	End limit on spool		
		0.0031	0.0028	1.0000	0.0004	0.0000	One-side fixed orifice clogging		
		0.0019	0.0000	0.0002	0.9989	0.0097	Spool wear		
		0.0008	0.0024	0.0024	0.0009	0.9887	Zero position misalignment		

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