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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (18): 4744-4747, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.4744.4747

Research on Pipeline Defects Identification Method based on RBF Neural Network

[1]Zhang He, [2]Deng Zhen and [3]Ge Liang
School of Electronic and Information Engineering, Southwest Petroleum University,
Chengdu, 610500, Sichuan, China

Abstract: Pipelines provide the most economical means of carrying oil and gas. Pipeline transportation has become one of the five biggest transportation businesses which plays an important role in national economy and production. Through the laboratory simulation software ANSYS to establish the pipeline defect two-dimensional simulation model, according to the magnetic flux leakage detection signal selecting appropriate parameters of pipeline defect identification. Based on the RBF artificial neural network of pipeline defect quantitative identification, the experimental results show that this method is used to predict the pipeline defect of high accuracy and can be applied to pipeline defect quantitative prediction. And Provide theoretical basis for identifying the choice of methods and application.

Key words: Pipeline defect, magnetic flux leakage detection, rbf neural network, detection

INTRODUCTION

As is important facilities of gas, petroleum and other media delivery, oil and gas pipelines play an important role in production of oil and gas field. In our country, nearly 75% of crude oil, 100% of natural gas is transported by pipelines and by the end of 2009, the total length of the oil and gas pipelines which have been built was approximately 69100 kilometers. At present, China's oil and gas pipelines' development (Ge and Sun, 2007) is at an unprecedented rate and it is estimated that by the end of 2015, the length of oil and gas pipelines in China can be reached to 110000 km (Han, 2007). Currently, there are more than 50% of the pipe network tending to aging and also nearly half of the oil and gas pipeline in our country have been in operation for more than five years, pipeline leaks caused by corrosion, wear, accidental damage and other causes occur frequently (Jin and Que, 2005; Yang, 2005; Chu, 2011; Chen, 2009). China spends as high as hundreds of millions of RMB on maintenance costs of oil and gas pipeline to prevent malignant accidents caused by corrosion perforation, pipes detonation and other causes each year and the cost is increasing gradually. The working conditions where industrial pipes are in operation are usually very poor, corrosion and fatigue damage of pipelines can happen easily, its internal latent defects can develop into damage and cause leakage accident (Naylor, 1998). Nowadays, an important direction of development of nondestructive testing is to use intelligent detectors to implement pipeline detection and by analyzing the signals detected to determine the defect size and other characteristics (Song *et al*., 2004). This study is based on the principle that using magnetic flux leakage testing to detect pipeline defects, establishes the two-dimensional simulation model of the pipeline defects and puts forward the corresponding RBF neural network quantitative identification method (Yang, 2005).

RBF NEURAL NETWORKS

Characteristics of RBF neural network: Radial Basis Function (RBF) network was proposed by Powell (1985), it is a kind of feed-forward network based on the function approximation theory. RBF network can approximate any nonlinear function, handle system's internal regularity which is hard to be analyzed and has a fast learning convergence speed, therefore, it is used widely.

Network structure of radial basis function: The radial basis function neural network consists of three layers; the structure is shown in Fig. 1. The input layer nodes transmits the input signals to the hidden layer, hidden layer nodes described by the Gaussian Kernel function (radial basis) and the output layer nodes are usually replaced by simple linear functions (Narimani *et al*., 2009). Effect-function (Kernel function) of the hidden layer nodes (perception unit) will generate a response to the input signal locally that is when the input signal close to the center range of the kernel function, the hidden layer nodes will produce a large output, therefore, the local approximation network of the Radial Basis Function Neural Network (RBFNN) has a fast learning speed, its base function is commonly used Gaussian function and it is usually written as:

Corresponding Author: Zhang He, School of Electronic and Information Engineering, Southwest Petroleum University, Chengdu, 610500, Sichuan, China

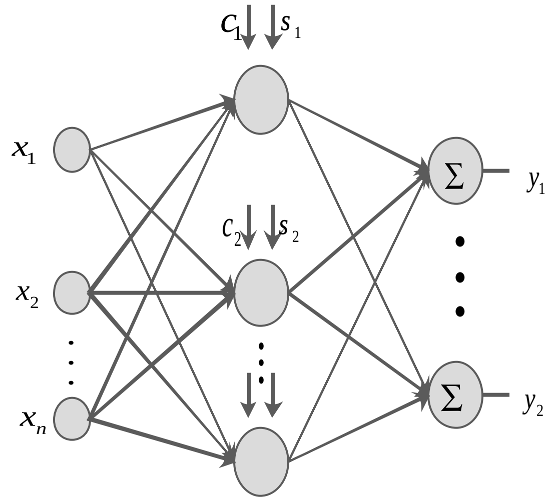

Fig. 1: Radial basis function network structure diagram

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

Where:

- $a_i(x)$ = i-th output of the hidden layer nodes
- x = Input samples, $X = (x_1, x_2,\dots, x_n)^T$
- c_t = i-th hidden layer node as the center of the Gaussian kernel function and has the same number of dimensions as x
- σ_i = Variable of the i-th hidden layer node, called normalization constant, or base width
- m = Number of hidden layer nodes RBF network's output

Layer $Y = [y_1, y_2,\dots, y_n]$ consists of n nodes, is given by:

$$y_n = \sum_{i=1}^{m} w_{in}\alpha_i(x) \quad n=1, 2,..., p \tag{2}$$

In which, p is the number of hidden units, w_{in} is the connection weight between the i-th hidden layer neurons and the n-the output layer neurons (Chen, 2009).

ORGANIZATION OF LEARNING SAMPLES

We use ANSYS software to establish the pipeline two-dimensional finite element model and through the simulation to get MFL signals of pipeline defects. The most important parameter to evaluate pipeline defects is the length and depth of the defects, the sample data required for the experiment is obtained by detecting the artificial defects and the shape of the defects are rectangular and circular. These defects generate corresponding magnetic flux leakage signals that are used as training samples of RBF neural network (Han, 2007).

Table 1: Several network training samples

Sequence	a	b	Vpp (mV)	Wp (mm)	Vpp (Wp)
11	0.5	0.8	0.0434	2.550	0.0170
21	1	1	0.0529	2.632	0.0201
31	1	4	0.1567	3.6685	0.0427
41	2	2.5	0.1162	3.7067	0.0313
51	2	4	0.1934	4.0139	0.0482
61	3	3.5	0.2016	4.2683	0.0472
71	3	5	0.2653	4.463	0.0594
75	4	5	0.2840	4.5867	0.0619

Selection of the defect's characteristic parameters: After pretreating the magnetic flux leakage signals collected by simulation, several major characteristic parameters extracted like value of peak to peak Vpp, width of peak to peak Wp (mm) and Vpp/Wp are used as characteristic defect's width of the sample we made changes from 0.5-5 mm and depth b changes from 0.5-6 mm. The defect made in the laboratory has 80 different parameters, its width has eight different values and in the case of each specific constant width, the depth b of the defect has 10 different parameters. Several network training samples are summarized in Table 1.

The neural network's input values are the parameters of the defect and the output of the network is the corresponding magnetic flux leakage signals. Regard the 60 samples as training samples and then we train the neural network. The rest of 20 samples are used as test samples to test the trained neural network.

Training and testing of the RBF neural network: Gaussian transfer function Radbas is used as RBF neural network's input in the hidden layer and linear transfer function Purelin is adopted in the output layer. The specified error index is 0.0001, extended constant is set to 1.2, the maximum number of neurons is 1000 and the number of neurons added between the two displays is 1. Before network training, we should perform data normalization processing and then proceed to the training of the network parameters. Figure 2 shows the training process of RBF neural network, after a 40-step training, target error reaches to 0.0001 and the mean square error of target value and simulation value is 6.79392×10^{-5}, repeat training and the results are the same and thus we complete the training of the network parameters.

To compare the RBF neural network training's speed with detection effect, the same learning samples are used as the BP neural network's input, hyperbolic tangent S-type transfer function Tansig is adopted in the hidden

Table 2: Correlation table of several sample parameters

Predicted output		RBF actual output		Absolute error		BP actual output		Absolute error	
Defect's width	Defect's depth	Defect's width	Defect's depth	Defect's width	Defect's depth	Defect's width	Defect's depth	Defect's width	Defect's depth
0.5	2.5	0.4999	2.5000	-0.0001	0.0000	0.4059	2.6054	-0.0941	0.1054
1.0	0.5	1.0013	0.4994	0.0013	-0.0006	1.0289	0.4964	0.0289	-0.0036
1.5	1.0	1.5032	0.9986	0.0032	-0.0014	1.5151	1.0785	0.0151	0.0785
4.0	6.0	3.9943	6.1724	-0.0057	0.1724	4.0204	5.7362	0.0204	-0.2638
5.0	5.0	5.0011	4.9899	0.0011	-0.0101	4.5930	4.9356	-0.0307	-0.0644
5.0	5.0	5.0011	4.9899	0.0011	-0.0101	4.5930	4.9356	-0.0307	-0.0644

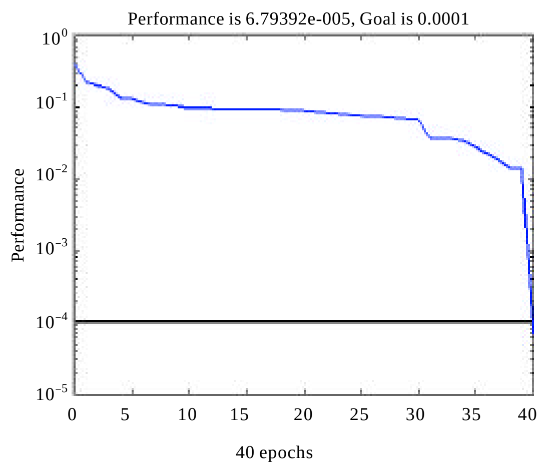

Fig. 2: Training process of RBF neural network

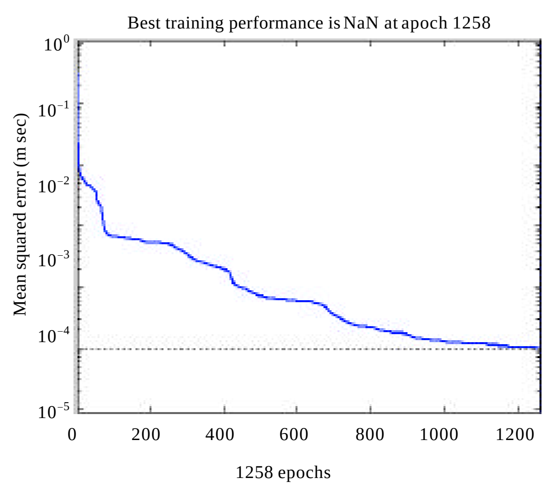

Fig. 3: Training process of BP neural network

layer, the linear transfer function Purelin is used in the output layer, the number of hidden layer's neurons is set to15 and error index is still 0.0001. Before training, it still needs for a data normalization processing. Figure 3 shows the training process of BP neural network, after 1258 iterations, the error function reaches to 0.0001. And through repeated training, in addition to the number of the training steps is different, the mean square error of the target value and simulation value reaches to 9.900×10-5. Several test results are shown in Table 2.

From Table 2, the following conclusions can be obtained through the comparison of the two methods' predictive results:

- By using the same sample data for learning, both of the two kinds of neural network can obtain relatively accurate test results and have a higher estimating precision of defect's size, this shows that both of them can realize detection and estimation of pipeline defects reliably and effectively
- The absolute error that produced by using RBF neural network to estimate the defect's size of the test data is 0.0000~0.1724, the relative error is about 3%, there are individual anomalies. And the absolute error that produced by using BP neural network to estimate the leakage's size of the test data is 0.0018-0.3941, its relative error is about 10%. In contrast, the former has a higher detecting precision on pipeline defect recognition

CONCLUSION

The intelligent and quantitative pipeline defect recognition is the difficulty of pipeline defect detection technology. The experimental results show that pipeline defect quantitative identification error of the RBF neural network is about 3%. Though RBF neural network has the existence of individual exception, compared with the BP neural network, it has a faster learning speed, can improve the precision and accuracy of detection effectively and realizes the intelligent and quantitative pipeline defect recognition.

ACKNOWLEDGMENTS

This study is supported by Foundation of Sichuan Educational Committee (Research on pattern recognition, No. 12ZB342) and Oil and Gas Pipeline Detection Technology Research Based on Multi-sensor Data Fusion (No. 2012XJZ021), the project is founded by

Technology Research Dept. CNOOC Research and 2012 Youth Foundation of Southwest Petroleum University.

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