ARTIFICIAL NEURAL NETWORK BASED CLASSIFICATION OF AUSTENITIC STAINLESS STEEL WELD DEFECTS IN TOFD TECHNIQUE

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Abstract

In this paper, an automatic detection system to recognize welding defects based on Time of flight diffraction technique is described. The proposed classification consists in detecting the four types of austenitic stainless steel weld defects and non-defect type. The austenitic stainless steel welds with artificially created defects have been considered. A scan Signals are obtained by conducting TOFD experiment on these weld defects. To improve the efficiency of defect detection, a discrete wavelet transform based denoising was also adopted as a preprocessing technique. Time scale features have been extracted from the denoised TOFD signals and an artificial neural network for weld defect classification was developed. A multi layer feed forward network with BFGS quasi-Newton back propagation has been applied for classification of the signals. The effect of hidden layers on the network was analyzed. The optimum performance function for this network was also found.

Keywords**:** *BFGS quasi-Newton back propagation., time scale features, classification accuracy, performance function*

I .INTRODUCTION

In spite of adopting the advanced techniques in welding technology, defects do occur in the welds.[1]. Many Non Destructive Techniques are used to ensure the welding quality. The TOFD technique is commonly used for weld inspection.[2] The two ultrasonic angle probes are used in the TOFD experiment. One is transmitter and another one is receiver as shown in Fig 1. The lateral wave runs along the surface, the back wall echo reflects the bottom surface of the test object and reach to the receiver. The other two signals, upper flaw tip diffracted signal and lower flaw tip diffracted signal appear due to in homogeneity.[3]

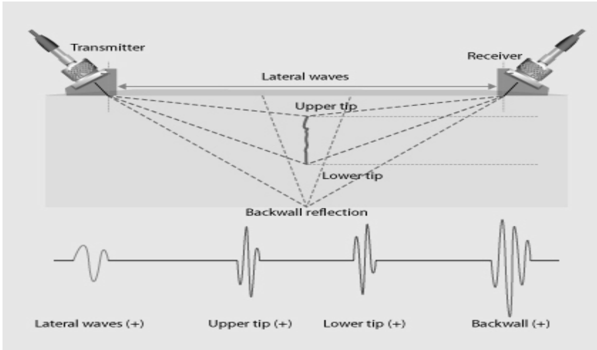

Fig1. TOFD System

Austenitic stainless steels have an austenitic, Face Centered Cubic (FCC) crystal structure. Austenitic stainless steel material is used for manufacturing the safety vessels of prototype fast breeder reactor (PFBR). In this paper, TOFD technique is applied on austenitic stainless steel weld defects and an algorithm based on neural network is developed to classify the weld defects. Neural networks use algorithms that learn functions, such as pattern recognition, creation of associations learning by training. [4]. Many researchers have explained that the Artificial Neural networks are suitable for classifying weld defects. S. Sambath et al., [5] proposed a Scaled conjugate gradient back propagation neural network for weld defect classification of pulse echo signals. E P de Moura, et al.,[6] followed a hierarchical and non hierarchical linear discriminator for classifying the weld defects. J. L. B. C. Veigav et al.,[7] has developed a feed forward back propagation network with one hidden layer. But, This paper presents a quasi-Newton back propagation artificial neural network model for classifying the defects of austenitic stainless steel weldments. In this work, the number of hidden layers are also increased from 2 to 6 and the classification performance is evaluated. Two performance functions were also adopted to obtain a better classification efficiency. The paper is structured as follows. Section II describes the data acquisition module. Section III deals with denoising. Section IV deals with ANN modeling. Section V describes results and discussion. Conclusion and future scope is discussed in section VI.

II .Data Acquisition

Five austenitic stainless steel welds with the dimension of 200 x 200x 25mm^3 of Double V Butt joint configuration are fabricated by shielded metal arc welding process. Four defects such as lack of fusion, lack of penetration, slag and porosity have been inserted into the four weldment respectively. One weldment has been fabricated without any defect. Using µTOFD of AEA Technology ,TOFD Experiment is conducted on these five weldments. Radiography technique is used as a reference for ensuring the defect types. 40 A scan signals of each defect have been acquired.

III .Denoising

A scan signals are undergone an optimum denoising method , using discrete wavelet transform. An analysis have been performed to develop an optimum denoising method for the A scans of five different defects. Symlet 4 with the 5^{th} decomposition level in association with the hard thresholding is found as the effective signal denoising algorithm for all the 5 different types of defected TOFD signals.[8] All the A scan signals are denoised using the above algorithm. Figure2,3,4,5,&6 show the A scan signals and the denoised A scan signals for all the types of defects.

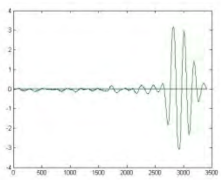

Fig2.a. OriginalSignal of no defect

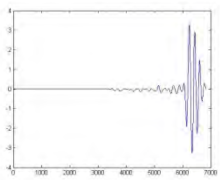

Fig2.b. Denoised Signal of no defect

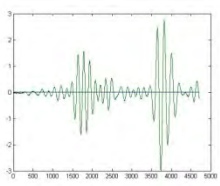

Fig3.a. OriginalSignal of LP defect

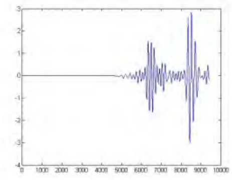

Fig3.b. Denoised Signal

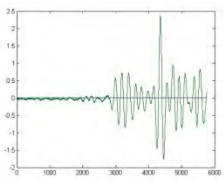

Fig4.a. Original Signal of LF defect

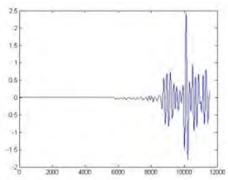

Fig4.b. Denoised Signal of LF defect

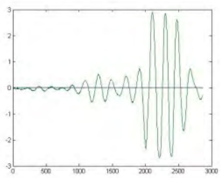

Fig 5.a. Original Signal of Porosity

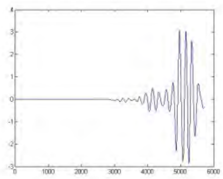

Fig 5.b. Denoised Signal of Porosity

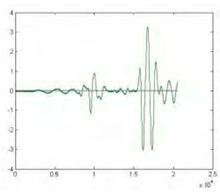

Fig 6.a. Original Signal of Slag

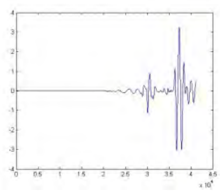

Fig6.b. Denoised Signal of Slag

IV . ANN Modeling

a. Feature Extraction

30 signals were used for training the network and the remaining 10 are used for testing the network. Single scale statistical features like mean, mode, median, standard deviation, maxima and minima are extracted from the denoised signals and are fed as inputs to the neural network.

b. Neural Network

The multi-layer back-propagation neural network is best suited for the engineering applications.[9]. Many researchers proved that the multi-layer back propagation with three layers can perform arbitrarily complex classification. [10,11] Back propagation Neural Network Topology with four hidden layers is shown in figure7.

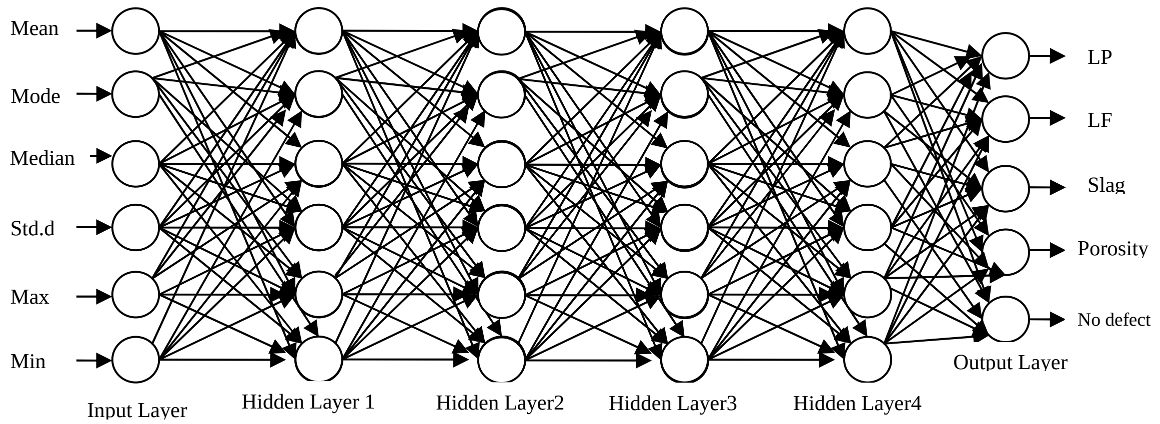

Fig 7. Back propagation Neural Network Topology with four hidden layers.

Propagation of data takes place from input layer to the output layer. In supervised learning the network is presented with a series of matched input and output patterns and the connection strengths or weights of the connections automatically adjusted to decrease the difference between the actual and desired outputs. Patterns are presented to the network and a feedback signal which is equal to the difference between the desired and actual output is propagated backwards through the network for the adjustment of weights of the layers' connections according to the back propagation learning algorithm. Trainbfg is a network training function that updates weight and bias values according to the BFGS quasi-Newton method. In this network, the Transfer function of hidden layers is chosen as Symmetric sigmoid transfer function and Linear transfer function for output layer. Gradient descent with momentum weight/bias learning function is chosen as back propagation weight/bias learning function. The network has been tried with both mean squared error performance function(MSE) and mean squared error with regularization performance function (MSEREG)

V. Results and discussion.

The training function, transfer function and learning function are kept unchanged for all the types of architecture. The hidden layers are increased from 2 to 6 and the classification performance is measured and tabulated in terms of percentage. To evaluate the efficiency of performance function on the network, MSE and MSEREG has been used one by one.. Table 1 shows the classification accuracy for the 2 different performance functions

Table 1. Classification accuracy in percentage with respect to performance function

Performance Function	**No of hidden layers**	**Training**	**Testing**
MSE	2	72	50
	3	60.7	38
	4	84	46
	5	86	44
	6	80	42
MSEREG	2	51.3	34
	3	68.7	46
	4	54	38
	5	20	20
	6	20	20

It is found that the mean squared error performance function (MSE) performed well, compared to the mean squared error with regularization (MSEREG). The classification performance of MSE in detail is shown in Table 2. It is observed that the network with MSE and hidden layers 4 and 5 gives better classification accuracy. The results also reveal that classification accuracy is more in case of training and poor in testing.

Table 2. Classification accuracy in percentage with MSE

	No of hidden layers									
	2		3		4		5		6	
Defect Type	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Lack of penetration	86.7	60	86.7	40	73.3	20	70	40	96.7	50
Lack of fusion	40	0	56.7	50	90	40	90	50	53.3	30
No defect	60	80	0	0	76.7	50	76.7	90	76.7	60
Porosity	80	70	76.7	50	80	50	100	20	80	40
Slag	93.3	40	83.3	50	100	70	93.3	20	93.3	30
Overall	72	50	60.7	38	84	46	86	44	80	42

VI . Conclusion

The TOFD A scans are obtained from defected austenitic stainless steel welds. Discrete wavelet transform based denoising was performed on these A scans. Six time scale statistical features were extracted from the denoised A scans. The features are fed as input signals to Neural Network, which was designed to classify the defects. BFGS quasi-Newton method has been applied as training algorithm. By increasing the number of hidden layers, the architecture is varied to enhance the defect classification detection of the network. The optimum performance function was identified as MSE, compared with MSEREG. It is observed that the network designed with 5 hidden layers performed well with a classification percentage of detection as 86% in training and 44% in testing. It is found that testing performance is not quite good as that of training performance. To improve the testing performance, the training algorithm can be modified. Instead of single scale features,. multi scale features can also be employed.

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