

Classification of TOFD Signals by Artificial Neural Network

Lalithakumari.S,¹ Sheelarani. B ², Venkatraman. B ³

^{1 & 2}Sathyabama University, Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai 600119, India
E Mail : lalithavengat@gmail.com

³Indira Gandhi Center For Atomic Research, Kalpakkam - 603102, India

Abstract

TOFD is one of the advanced ultrasonic NDE techniques widely used in weld inspection. Signal and image evaluation in TOFD requires adequate knowledge and experience. It is well known that artificial neural networks can be used for defect classification and sizing. However, review of literature indicates that very little work has been done in the area of application of ANN for TOFD signals and images. This work focuses on the application of multi layer feed forward network with Levenberg-Marquardt algorithm for the classification of TOFD signals from defect types such as Lack of Fusion and Lack of Penetration. TOFD signals from austenitic stainless steel weld pads with the above mentioned defects were acquired using an AEA micro plus TOFD equipment. Time scale features were extracted from the resultant TOFD A scans. Increasing the number of hidden layers in the network from 0 to 4 resulted in classification accuracy better than 95%. The results are a pointer to the promising application of this for automatic defect classification by TOFD technique. This paper provides the approach and analysis methodologies and the results obtained.

Keywords: Levenberg-Marquardt algorithm, time scale features, classification accuracy,

1. INTRODUCTION

Welding is a process which is used to join two metal pieces. In spite of the advanced techniques followed in welding process, defects do occur in the welds. This is due to the number of process parameters, which make it difficult to achieve a defect free weld.[1]. Non Destructive Techniques are adopted to ensure the quality of welding. The TOFD technique is one of the efficient method which is widely used for automatic weld inspection [2]. The ultrasonic TOFD technique employs two probes, a transmitter and a receiver, in which diffracted energy characterizes the weld defects. Even though, The TOFD technique affords high speed data, the crucial processes of data processing and interpretation are still performed manually. It needs skilled operator to achieve consistency and reliability.[3]. Austenitic stainless steel materials have been chosen as the major structural materials for manufacturing the safety vessels of prototype fast breeder reactor (PFBR), in view of their adequate high temperature mechanical properties, compatibility with liquid sodium coolant, and satisfactory experience in the use of these steels for high temperature service. In this paper, TOFD technique is applied on austenitic stainless steel weld defects and neural network based algorithm is developed to classify the weld defects. Neural networks use algorithms, which learn pattern recognition and creation of associations learning by training. The neural networks can process enormous amounts of data in a short period of time [4]. Some researchers have revealed the ability of Artificial Neural network for classifying weld defects. S. Sambath et al., [5] proposed a neural network based weld defect classification of pulse echo signals. E P de Maura, et al.,[6] used a hierarchical and non hierarchical linear discriminator for classifying the weld defects. J. L. B. C.



Veigav et al.,[7] has designed a feed forward back propagation network with one hidden layer. Feed forward Multi layer perceptron ANNs with varying topologies were simulated in software and trained by Shaun W. Lawson et al [8]. C'Shekhar N Shitole [3], developed neural-fuzzy classifier. But, This paper presents a feed forward back propagation neural network, which is meant for classifying the defects of austenitic stainless steel weldments. In this work, the number of hidden layers is also increased from 0 to 4 and the classification performance is evaluated.. The paper is structured as follows. Section 2 deals with the data acquisition module and pre processing. Section3 discusses the proposed ANN modeling. Section 4 describes Results and discussion. Conclusion and future work is described in section 5.

2. DATA ACQUISITION

TOFD Experiment

Two austenitic stainless steel welds with the dimension of 200 x 200x 25mm³ are fabricated, with Double Vee Butt joint configuration and made by shielded metal arc welding process. The first weld pad had lack of penetration introduced during the welding process, second weld pad had lack of fusion. Experiments are performed using μ TOFD of AEA Technology, UK to detect the defect. The photograph of the experimental set up is also shown in figure2.



Figure 1 . TOFD Experimental Set Up.

A methodical approach has been adopted to ensure reliability of the experimental data by verifying it with radiography technique. The procedure adopted for testing includes calibration, job identification, visual inspection, scanning and defect identification. The resultant A scans are obtained.

Pre Processing

In order to improve the performance of neural networks, pre-processing of the TOFD A scan signals were carried out to smooth them before being given as the input for the neural network. The A scan signals are undergone an optimum denoising method, using discrete wavelet transform. An analysis have been done to find an optimum denoising method for the A scans of different defects[9]. The efficiency of the denoising methods are evaluated with their SNR values. Symlet 4 with the 5th decomposition level in association with the hard thresholding is found as the effective signal

denoising algorithm for the two different types of defected TOFD signals. All the A scan signals are denoised using the above algorithm.

3. ANN Modeling

Among the various types of neural networks, the multi-layer back-propagation neural network is suitable for the engineering applications.[10] The back-propagation network learns by back propagating the errors in the direction from output neurons to input neurons. The multi-layer network consists of an input layer, output layer and a number of hidden layers. The presence of hidden layers allows the network to represent and compute more complicated associations between patterns. Many researchers proved that the multi-layer back propagation with three layers can perform arbitrarily complex classification, while, the complexity depends on the number of neurons in the hidden layer. The number of neurons in each layer may be modified according to the application. [11]

Propagation of data takes place from input layer to the output layer. There is no connectivity between neurons in a layer. This type of neural network is trained using a process of supervised learning in which 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. To begin with, 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. Trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization . It is often the fastest back propagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms [12]. In this work, the statistical features of the A scans of defected welds are extracted and they are used as the input signals to the feed forward back propagation network with the Levenberg-Marquardt training algorithm. Transfer functions convert a neural network layer's net input into its net output. In this network, the Transfer function of hidden layers is chosen as Symmetric sigmoid transfer function 'tansig' and Linear transfer function, 'purelin' for output layer. Back propagation weight/bias learning function is chosen as gradient descent with momentum weight/bias learning function. Performance function is chosen as mean squared error performance function.

4. Results and Discussion

The number of hidden layers is increased from 0 to 4 and for each change in the architecture, the network is trained and the network performance is studied with the defect classification performance. The classification performance is tabulated according to the number of hidden layers. The classification performance is tabulated for 0, 1, 2, 3 and 4 hidden layers respectively in Table 1

Table 1. Classification Performance in percentage

No.of hidden layers	0	
Defect Type	Training	Testing
Lack of penetration	100	70
Lack of fusion	100	90
Overall	100	80
No.of hidden layers	1	
Defect Type	Training	Testing
Lack of penetration	100	80
Lack of fusion	100	80
Overall	100	80
No.of hidden layers	2	
Defect Type	Training	Testing
Lack of penetration	100	80
Lack of fusion	100	70
Overall	100	75
No.of hidden layers	3	
Defect Type	Training	Testing
Lack of penetration	100	70
Lack of fusion	100	80
Overall	100	75
No.of hidden layers	4	
Defect Type	Training	Testing
Lack of penetration	100	60
Lack of fusion	100	90
Overall	100	75

5.Conclusion

The TOFD experiment is conducted on defected austenitic stainless steel welds and statistical features were extracted from the resultant A scans. The features are given as input signals to the Feed forward Back propagation Neural Network, which was designed to classify the defects. Various types of architecture were designed to improve the classification performance of the network. It is observed that the classification performance is maximum, but, the testing performance is not quite promising compared to training performance. In order to improve the testing performance, the training algorithm can be changed. The classification accuracy can also be improved by extracting the multi scale features instead of single scale features.

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