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Automatic Defect Classification in Ultrasonic NDT Using Artificial Intelligence

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Abstract A methodology is developed to detect defects in NDT of materials using an Artificial Neural Network and signal processing technique. This technique is proposed to improve the sensibility of flaw detection and to classify defects in Ultrasonic testing. Wavelet transform is used to derive a feature vector which contains two-dimensional information on various types of defects. These vectors are then classified using an ANN trained with the back propagation algorithm. The inputs of the ANN are the features extracted from each ultrasonic oscillogram. Four different types of defect are considered namely porosity, lack of fusion, and tungsten inclusion and non defect. The training of the ANN uses supervised learning mechanism and therefore each input has the respective desired output. The available dataset is randomly split into a training subset (to update the weight values) and a validation subset. With the wavelet features and ANN, good classification at the rate of 94% is obtained. According to the results, the algorithms developed and applied to ultrasonic signals are highly reliable and precise for online quality monitoring.

Keywords Ultrasonic testing · TIG welding · Defect classification · Wavelet transform · Artificial neural networks

1 Introduction

Ultrasonic methodologies are the most practically feasible NDT applications in the area of material characterization. Ultrasonic testing is used extensively throughout the industry for quality assessment and detection of defects in engineering materials. In ultrasonic testing useful information about integrity or geometry of the object under test is obtained. Measurement configuration often encountered in NDT includes pulse-echo reflection technique. The ultrasonic wave, generated by a piezoelectric transducer propagates through the material and is reflected by defects and back surface of the sample. The signals reflected by defects possess information about defects size and orientation.

The main aim of ultrasonic inspection of engineering materials is the detection, location and classification of internal flaws as quickly and accurately as possible. Despite the advantages of the ultrasonic technique, a high velocity of inspection, high probability of detection, and low number of false results, the classification of defects based on ultrasonic signals is still frequently questioned, since the analysis and the identification of defect types depend exclusively on the experience and knowledge of the operator. The correct classification of the type of flaw present in the material reduces measurement errors, increasing the confidence in the test and consequently the safety of the material in future application. The progress in computational techniques, specifically the development of neural networks, has greatly stimulated the research into the development of automatic systems for the inspection and the classification of defects in engineering materials [1–8].

2 Previous Related Work

In Ref. [1], an artificial neural network model was developed for the pulse echo technique to classify resistance spot welds in four quality levels. They used a back-propagation multilayer feed forward ANN with Levenberg–Marquardt

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training algorithm for this classification. Input of the ANN is a 10-component vectors, that contain the relative heights of the echoes and the distance between consecutive echoes. They achieved the success rate of 100% when $\delta > 0.25$. In Ref. [2], an ANN model was developed for fault detection in not accessible pipes. Fault classification was based on the depth and width of the faults and the signal database for the training, validation and test set were obtained using finite element simulations based on propagation of guided ultrasonic waves. Their results showed that the percentage error of ANN for fault width classification to be less than 5% and less than 7% for fault depth classification. In addition to experimental works, numerical simulations were also used to generate ultrasonic signals for flaw detection using neural networks. In Ref. [3], the authors evaluated the application of ANN for pattern recognition of ultrasonic signals in weld defects using pulse echo and TOFD techniques. They classified four welding defects by using supervised feed forward back propagation type neural network. They reported the success rate of 72.5% for pulse echo and 77.5% for TOFD technique, both without preprocessing. In Ref. [4], the wavelet transform has been successfully used in experiments to suppress noise and enhance flaw location from ultrasonic signals, with a good defect localization. The obtained result was then fed to an automatic Artificial Neural Network classification and learning algorithm of defects from A-scan data. In Ref. [5], using the TOFD technique the authors classified three kinds of welding defects based on signal processing techniques and artificial neural network. The Fourier transform and wavelet transform were used for preprocessing A scan signals. They implemented linear pattern classifiers into the network. In comparison with Fourier transform, Wavelet transform results in better classification. In Ref. [6], the authors tried to distinguish between a planar and volumetric flaw based on the calculation of wavelet coefficients, time and frequency domain parameters to characterize the defects. Classification was performed using K nearest neighbor, Bayesian statistical method and artificial neural network. They reported higher classification accuracy of 97% with features from wavelet transforms associated with ANN. In Ref. [7], a methodology was developed to detect defects obtained from ultrasonic-based NDT using the multilayer perceptrons (MLP). The authors found that results obtained by using discrete wavelet transform (for feature extraction) and neural networks were superior over the classification of NDT signals using only neural networks. In Ref. [8], an evaluation of various types and configurations of neural network developed for the purpose of assisting in accurate flaw detection in steel plates is illustrated. The presented research was conducted using a wide range of samples, including non-defective plates, plates with side-drilled holes, different inclusions and porosity, together with smooth and rough cracks. The obtained results indicated that significant benefits may be obtained from the techniques demonstrated with no form of feature extraction employed. The authors also suggested that the implementation will have to move to Digital signal processing architectures in order to realize practical solution.

In the present research, signal processing technique based on wavelet transform [9, 10] is applied in order to enhance the sensibility of flaw detection to characterize defects in nature (/porosity/lack of fusion/tungsten inclusion/non defect). Features for discrimination can be extracted using the discrete wavelet transformation [11]. An algorithm based on wavelets is developed in order to enhance flaw visibility. An artificial neural network combined with signal processing technique is applied to solve problems in the interpretation of ultrasonic oscillograms obtained by the pulse echo method. An ANN classifies varies types of defects through their respective ultrasonic oscillograms.

In this study, ultrasonic signals were acquired using the pulse echo technique during weld bead inspection with three (3) different kinds of defects: porosity (PO), lack of fusion (LF), and tungsten inclusion (TI). One class of signals from regions presenting no defect (ND) to identify signals from welds with defect or welds that presented no defects.

3 Experimental Procedure

The Research work was carried out in the following steps:

- Collecting certain number of ultrasonic oscillograms for different type of defects and their digitalization.
- Extracting the features by using signal processing technique called wavelets.
- Training the artificial neural network (ANN) to classify defects.
- Testing the trained network for verification.

3.1 Material

In the pulse echo technique, inspections were performed on nine test specimens made of stainless steel plates of 5 mm in thickness and 200 mm in length. Different defects such as porosity (PO), lack of fusion (LF), and tungsten inclusion (TI) were inserted into the test samples during the TIG welding process, generating pattern defects. The type, position and size of each inserted defects were recorded through the use of radiographic tests of the weld beads.

3.2 System Configuration for Capturing the Ultrasonic Signals

The PC based ultrasonic testing system developed in this work consists of UFD15 ultrasonic flaw detector with piezo-

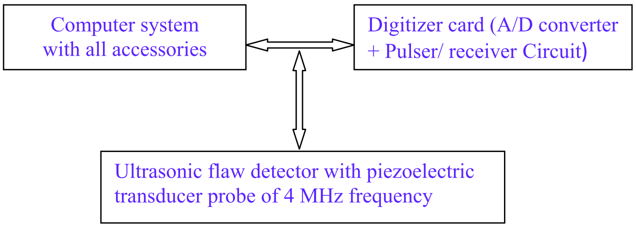


Fig. 1 PC based ultrasonic testing system

electric transducer probe of 4 MHz frequency, computer system with all accessories and a digitizer card with control program which is shown in Fig. 1. The digitizer card includes pulser/receiver circuit and an A/D converter. Pulser/receiver circuit generates the trigger pulse and transfers it to the ultrasonic flaw detector by means of piezoelectric transducer by PC. The ultrasonic flaw detector gets the trigger pulse and converts it into ultrasound vibrations and vice versa for making the examination of materials. The software developed ULTIMA 200S carries out the control of the device, preprocesses the signals and stores the signals from the region of the weld being inspected.

3.3 Acquisition & Selection of Signals

The PC based ultrasonic testing system is properly installed as shown in Fig. 1. In the Pulse echo ultrasonic testing, contact mode measurement is used to find the flaw in materials. The air gap between the specimen and probe is eliminated by applying the lubricant on the surface of the specimen and then screen calibration is done for proper measurement. The identification of flaw in the specimen is done by moving the probe along the surface of the specimen. In testing, an analog signal is displayed in the screen of ultrasonic flaw detector. Then the analog signal is converted to digital signal i.e. samples by using the A/D converter and stored in computer system. Since the digital signals are captured directly from the ultrasonic flaw detector through online conversion, preprocessing of the signals is also done by the digitizer card through the software. Ultrasonic flaw signals are acquired with a sampling frequency of 50 MSPS (Mega samples per second) and sample length of 4k (4096 points). Thus the PC based ultrasonic testing system can digitize ultrasonic flaw signals in real-time fashion.

After the inspection of nine test samples, the database was created consisting of a total number of 240 ultrasonic oscillograms (A-scans), equally divided into the four classes—lack of fusion (LF), porosity (PO), tungsten inclusion (TI) and one class of signals presenting no defect (ND). From the 240 signals, 190 signals were used for training the network, and remaining 50 signals were reserved to test the capability of the ANN to identify signals not presented during the training process.

4 Signal Processing

4.1 Wavelet Transform

Ultrasonic signals contain numerous non-stationary or transitory characteristics. These characteristics are often the most important part of the signal and Fourier analysis is not suitable to detect them since it can be processed only in frequency domain. The Wavelet Transform is developed especially to overcome these deficiencies. The signal analysis using Wavelet transform is faster than the Fourier transform analysis. The *Wavelet Transform* (WT) is the most recent technique for processing non stationary (transient) signals simultaneously in time and frequency domains [9, 10]. It is a windowing technique with variable-sized regions, which allows the use of long time intervals to obtain more precise low frequency information and shorter regions where high frequency information is needed [11]. Besides, Wavelet Transform is capable of decomposing a signal into shifted and scaled versions of the original (or *mother*) wavelet. Its application seems to be attractive for ultrasonic data processing, especially for detection of defects in grainy materials. In NDT it is applied for enhancement of detection of defects [4].

The Wavelet Transform decomposes signal $s(t)$ in a sum of elementary contributions called wavelets. The WT is the correlation between the signal and a set of basic wavelets. The daughter wavelets $\psi_{a,b}(t)$ are generated from the mother wavelet $\psi(t)$ by dilation and shift operations. The mother wavelet function is used to extract details and information in the time and the frequency domains from the transient signal under analysis.

The WT expansion coefficients $X_{WT}(a,b)$ of the signal $s(t)$ are given by:

$$X_{WT}(a,b) = \int_{-\infty}^{\infty} s(t)\psi_{a,b}(t)dt \tag{1}$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

The discrete wavelet transform (DWT) analyzes the signal by decomposing it into its coarse and detailed information.

4.2 Features Extraction

The purpose of S.MALLAT algorithm [12] is to extract characteristics from a signal on various scales proceeding by successive high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and detail coefficients calculated by S.MALLAT decomposition algorithm on different levels using DAUBECHIES window. The normalized signal of defect echo is characterized by wavelet coefficients which are the successive continuation of the approximation coefficients and detail coefficients. The basic feature extraction procedure consists of

1. Decomposing the signal using DWT into N levels using filtering and decimation to obtain the approximation and detailed coefficients
2. Extracting the features from the DWT coefficients.

Each defect signal is decomposed into four sub-bands using DWT and twelve features are extracted for each sub band of detail coefficients. The defect signal for porosity is shown in Fig. 2 and the representation of 1024 and 256 samples of DWT coefficients for porosity is shown in Fig. 3(a)–(b) respectively.

Figure 4 shows the defect signal for lack of fusion and Fig. 5(a) and (b) shows the representation of 1024 and 256 samples of DWT coefficients for lack of fusion respectively.

Figure 6 shows the defect signal for tungsten inclusion and Fig. 7(a) and (b) shows the representation of 1024 and 256 samples of DWT coefficients for tungsten inclusion respectively.

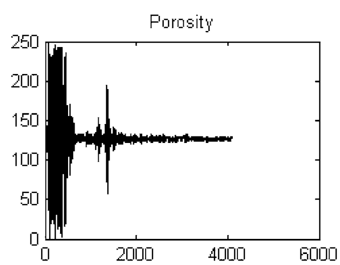


Fig. 2 Ultrasonic signal for porosity

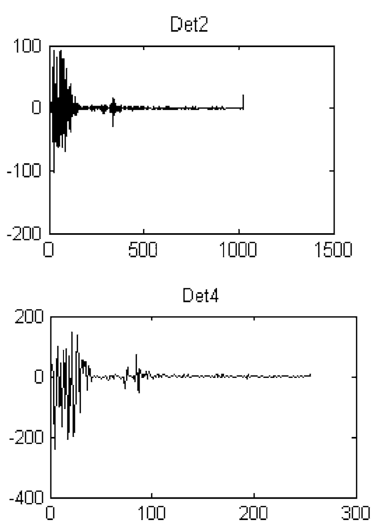


Fig. 3 DWT coefficients representation for porosity (**a**) 1024 samples, (**b**) 256 samples

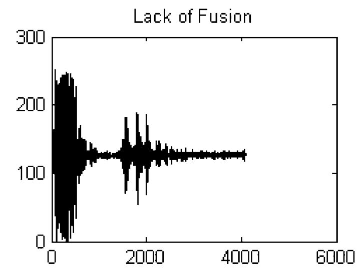


Fig. 4 Ultrasonic signal for lack of fusion

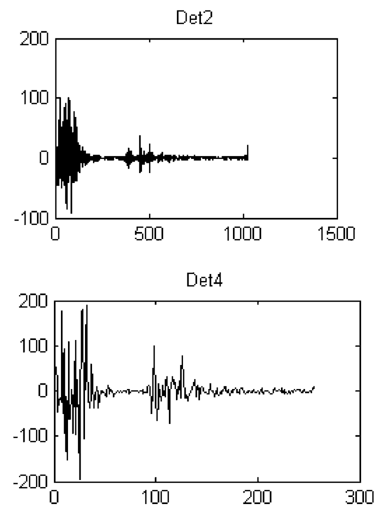


Fig. 5 DWT coefficients representation for lack of fusion (**a**) 1024 samples, (**b**) 256 samples

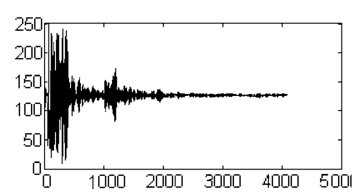


Fig. 6 Ultrasonic signal for tungsten inclusion

4.3 Wavelet Features

Features for discrimination of detected echoes are extracted in discrete wavelet representation. In this study, 12 features are extracted from the each signal of the four classes. The extracted features from the signal and their relationship are as below:

1. Mean $m = (\frac{1}{n}) \sum_{i=1}^{n} m_i$
2. Variance: $v = \frac{1}{n-1} \sum_{i=1}^{n} (m_i - m)^2$
3. Mean of the Energy Samples $m_e = (\frac{1}{n}) \sum_{i=1}^{n} m_i^2$
4. Maximum Amplitude
5. Minimum Amplitude
6. Maximum Energy Samples

Table 1 The extracted features from the detail coefficients in four sub bands

Extracted features	Detail coefficients of four frequency bands			
	$\pi/2-\pi$	$\pi/4-\pi/2$	$\pi/8-\pi/4$	$\pi/16-\pi/8$
Mean	0.2486	0.2477	0.5988	−1.2547
Variance	20.7566	152.2925	3455.12	982.6577
Maximum amplitude	49.4459	89.15	348.4967	147.7117
Minimum amplitude	−43.688	−92.3208	−316.102	−204.863
Maximum energy	2444.9	8523.135	121450	41968.95
Average frequency	2.453	1.8987	1.9256	1.5825
Minimum frequency	1.5984	1.988	1.2272	3.0925
Half point	2.1997	2.2948	2.4544	2.1844

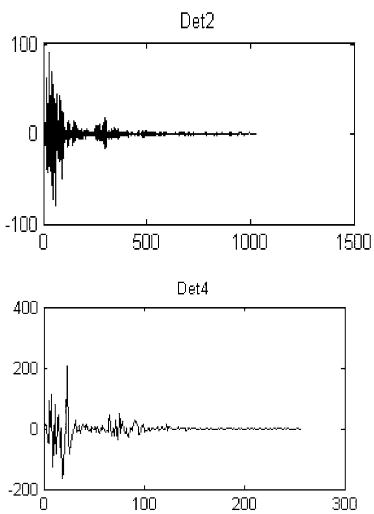


Fig. 7 DWT coefficients representation for tungsten inclusion (**a**) 1024, samples (**b**) 256 samples

7. Minimum Energy Samples
8. Average Frequency
9. Mid Frequency
10. Frequency of Maximum Energy Samples
11. Frequency of Minimum Energy Samples
12. Half Point of the function energy (HaPo): It is a very valuable variable as it represents the frequency that divides up the spectrum into two parts of same area.

Among the above 12 features, 8 (Nos. 1, 2, 4, 5, 6, 8, 11 and 12) are giving good discrimination between material defects. On the other hand, other features (Nos. 3, 7, 9 and 10) have very close values for all defects and hence it can be neglected. So in this study, a set of 8 features (which are the pertinent parameters for each type of defects) is calculated from the reflected echo of each signal. These eight features are taken as the input to the ANN. The extracted features from the detail coefficients in four sub bands for one of the porosity signal is shown in the Table 1.

5 Artificial Neural Network

MATLAB NN Toolbox is used for the design, implementation and simulation of the network with feed forward back propagation algorithm as explained elsewhere [13]. Back propagation networks (BPN) are multi-layer networks with the hidden layers of sigmoid transfer function and a linear output layer. The transfer function in the hidden layers should be differentiable and thus, either log-sigmoid or tan-sigmoid functions are typically used. In this study, the tan-sigmoid transfer function, ‘tansig’ is used for both the hidden layers and the output layer. They calculate a layer’s output from its net input. Each hidden layer and output layer is made of artificial neurons, which are connected through adaptive weights. The training function selected for the network is ‘trainscg’.

5.1 Proposed NN Structure

In this work, different combinations of layers and neurons were tried. Finally, a fully connected feed-forward neural network is selected with 8 input nodes, two hidden layers with 8 nodes and 25 nodes and an output layer with 3 nodes for classifying the four classes of signals. The proposed network architecture is shown in Fig. 8. The developed NN is trained several times until the number of neurons along with the initial weights and biases satisfies the error goal of $1e^{-2}$ [14].

5.2 Inputs of the Artificial Neural Network

The features extracted from each ultrasonic signal are used as the input of the artificial neural network by means of a MATLAB NN toolbox. The input of the ANN must be representative of its respective ultrasonic diagram. Here, the input of the ANN is 8 component vector. The following figures (Figs. 9–11) show the DWT coefficients representation of a defect signal (left) and its respective input of the ANN (right).

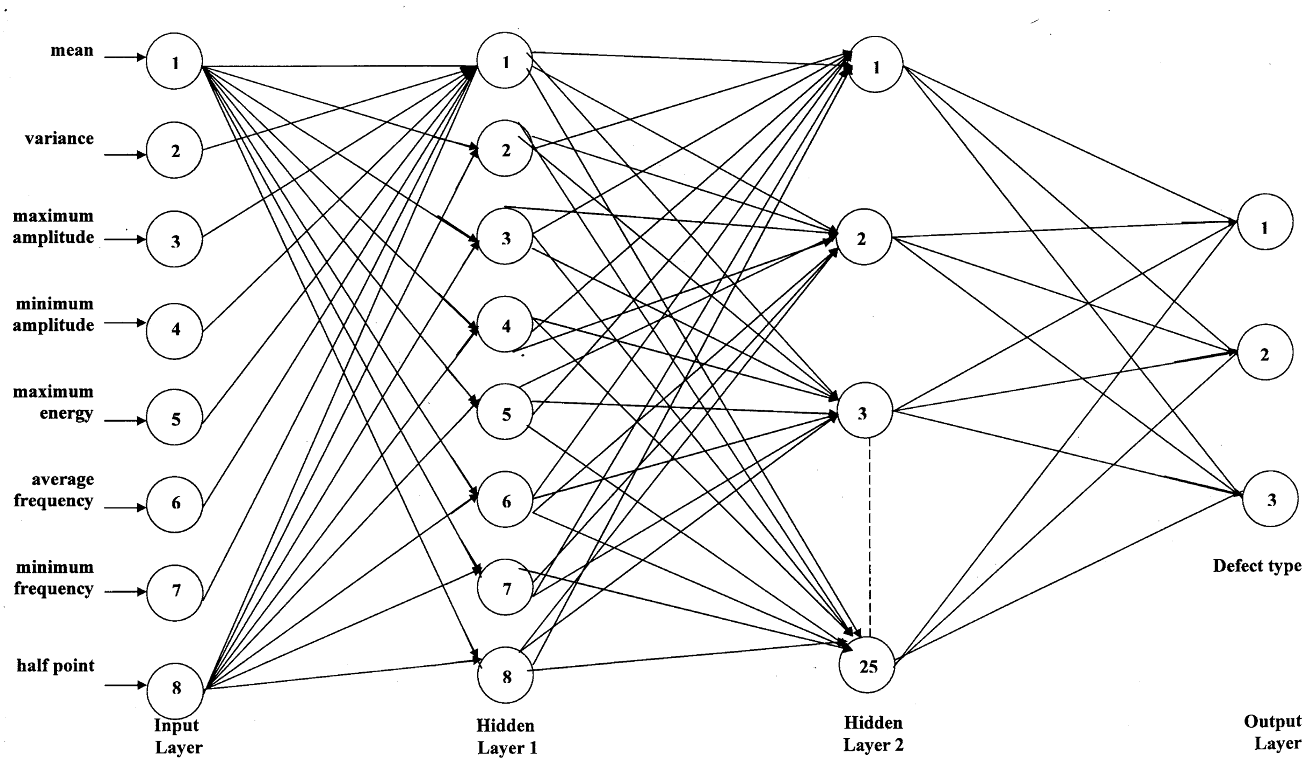
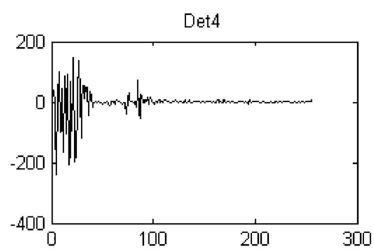


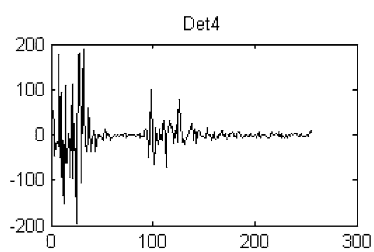
Fig. 8 Four layered back propagation NN topology

Fig. 9 DWT coefficients representation of a porosity signal (*left*) and its respective input of the ANN (*right*)



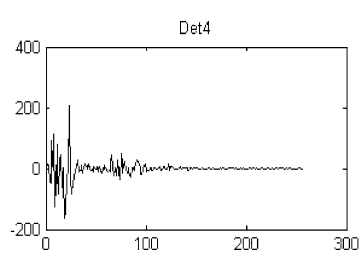
-0.0868	=	mean of the samples
391.0487		variance
334.3833		maximum amplitude
-368.506		minimum amplitude
135796.5		maximum energy
2.1982		average frequency
2.7658		minimum frequency
1.8914		half point

Fig. 10 DWT coefficients representation of a lack of fusion signal (*left*) and its respective input of the ANN (*right*)



-0.0168	=	mean of the samples
8.4244		variance
75.5202		maximum amplitude
-69.9053		minimum amplitude
5703.302		maximum energy
1.9681		average frequency
3.1002		minimum frequency
2.2672		half point

Fig. 11 DWT coefficients representation of a tungsten inclusion signal (*left*) and its respective input of the ANN (*right*)



-0.4579	=	mean of the samples
862.8073		variance
207.630		maximum amplitude
-162.666		minimum amplitude
43110.44		maximum energy
1.2853		average frequency
2.3011		minimum frequency
1.5953		half point

Table 2 Partial Sample data for training the NN model

Mean	Variance	Maximum amplitude	Minimum amplitude	Maximum energy	Average frequency	Minimum frequency	Half point	Half point
0.2486	20.7566	49.4459	−43.688	2444.9	2.453	1.5984	2.1997	Porosity
0.1762	110.6015	122.2586	−102.334	14947.16	1.8849	2.9391	2.0862	LF
0.369	1889.23	360.99	−376.41	141691.2	1.589	0.5737	2.3623	TI
0.2382	7.3178	32.5188	−43.1914	1865.496	2.1636	1.5217	2.3899	ND
0.2289	15.6674	44.6028	−41.8866	1989.408	2.3568	1.8592	2.1016	Porosity
0.422	2092.17	354.50	−378.63	143366.9	1.6018	0.0644	2.3976	TI
0.1701	2351.106	287.8484	−291.971	85247.29	1.9033	2.7489	2.4666	LF
0.2269	380.0493	159.8673	−118.856	25557.54	1.674	0.7609	1.7917	ND
0.308	3853.66	385.24	−395.57	156481.4	1.6564	2.1875	2.4912	TI
0.1183	178.2017	88.8235	−110.799	12276.35	1.9206	2.7796	2.3255	Porosity
0.2255	6.7074	31.496	−28.4516	991.998	2.3631	1.7733	2.1322	ND
0.0254	109.4518	85.5535	−105.279	11083.68	2.0705	1.2026	2.3562	LF

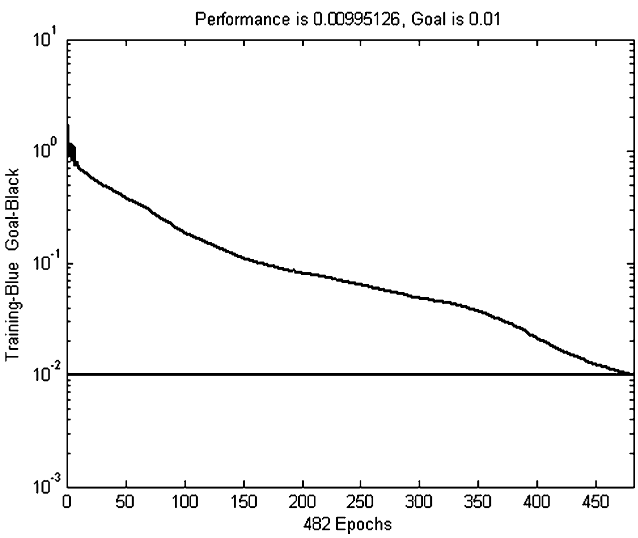


Fig. 12 The relationship between error value and number of epochs

5.3 Training and Testing

For a neural network to reliably classify defects, the training database must contain sufficient data to represent each type of defect for the training operation to be effective. A database is created to a total of 240 sets, consisting of 60 sets for each class. From these, 12 data sets for each class are selected at random to create a separate test set consisting of 50 sets which is used for testing the trained network. The partial sample data for training the NN model is represented in Table 2.

Before training the network, the above data were normalized suitably. The training data are fed into the network and after several iterations; the network delivered a converged result at a lesser epoch (Fig. 12). The weight values corresponding to the trained network are saved. These weight values are applied to another network having the same architecture as the trained network. Now the test data are fed into the network. Test data do not contain the data used for training the network.

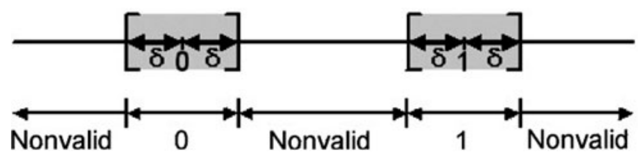


Fig. 13 Validity intervals for the components of output vectors

6 Results and Discussion

The aim is to get a well-trained ANN capable of performing the human expert's function and classify various defects from their respective ultrasonic oscillograms, so the ANN must have an appropriate ability to generalize.

The 50 input vectors used for cross validation are used for assessing the ability to generalize the previously trained ANN. An output is a three component vector. A component value in the $1\pm\delta$ interval is considered as 1 and a component value in the $0\pm\delta$ interval is considered as 0. Other values of components are considered non-valid [15] (Fig. 13).

The best five results based on goodness-of-fit criteria for the classification of four classes of defect are shown in Table 3. Optimal BPN architecture is selected based on the best classification results. Best result and the corresponding parameter values are shown in trial 2, after attempting with various parameters like number of neurons, activation function and training algorithm.

The input vectors are presented to the ANN that compares each experimental output vector with its respective target. Target values and ANN output values for 50 testing vectors are represented in a graphical form as Fig. 14.

Table 3 Selection of optimal BPN architecture for classification of four classes of defect

Parameters	1	**2**	3	4	5
No. of features	8	**8**	8	8	8
AF* (Hidden Layer 1)	tansig	**tansig**	tansig	tansig	tansig
AF (Hidden Layer 2)	tansig	**tansig**	tansig	tansig	tansig
AF (Output Layer)	tansig	**tansig**	tansig	tansig	tansig
Training algorithm	trainscg	**trainscg**	trainscg	trainscg	trainscg
No. of neurons (Layer 1)	8	**8**	12	14	15
No. of neurons (Layer 2)	22	**25**	26	30	24
Performance goal	0.01	**0.01**	0.01	0.01	0.01
Classification results (%)	92.00	**94.00**	90.00	92.00	88.00
BPN structure	8-8-22-3	**8-8-25-3**	8-12-26-3	8-14-30-3	8-15-24-3

*AF—Activation Function

Table 4 Table of success and errors—training and testing—preprocessed pulse-echo signals

Defect	Training		Testing	
	Success rate	Error rate	Success rate	Error rate
Porosity	100%	0%	92%	8%
LF	100%	0%	85%	15%
TI	100%	0%	100%	0%
Non defect	100%	0%	100%	0%
Total	100%	0%	94%	6%

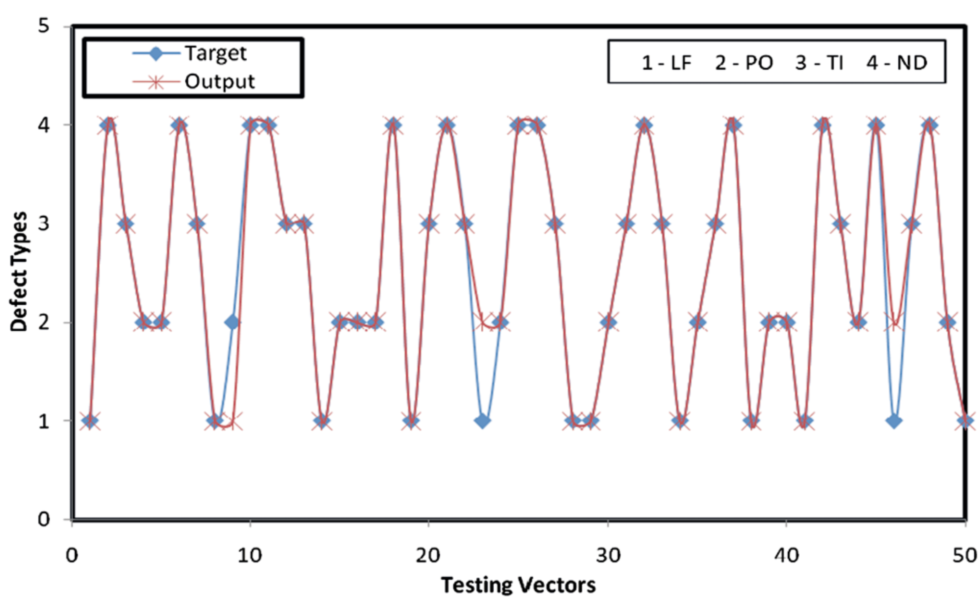


Fig. 14 Target values and ANN output values for 50 testing vectors

The results show that the ANN combined with DWT gives good classification accuracy at the rate of 94% (Table 4). DWT not only provides an excellent feature extraction method, it also provides significant data reduction, thereby reducing the computational burden considerably.

The selection of the significant parameters (features) of ultrasonic oscillograms in order to make the inputs of the ANN is very important. The way of representing the ultrasonic oscillograms by means of 8-component vectors that contain features extracted by wavelet transform is appropriate as discussed in this section.

7 Conclusions

In this paper, a novel method for classification of signals in NDT of materials is developed using ANN and DWT. The implemented configuration of ANN (An Artificial Neural

Network with signal processing technique) showed a reasonable rate of success to classify patterns of ultrasonic signals obtained from four classes of defect in stainless steel plates extracted by pulse echo technique. The ANN model develops a fast and user friendly system, which assists practicing technicians by reducing the time spent in classifying the defect signals obtained through ultrasonic testing.

The accuracy of the classifier is determined by the percentage of waveforms correctly identified. In this work, a good classification rate of 94% is obtained using ANN with wavelet features. The obtained classification accuracy for the detection and classification of defects are very encouraging, showing the suitability for the development of a decision support system for non-destructive evaluation of materials. The success rate of this method is higher compared to the other methods without signal processing. According to the results, it can be concluded that the model developed and applied to ultrasonic signals are highly reliable and precise for online quality monitoring.

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