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Artificial intelligence based defect classification for weld joints

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Abstract. This paper mainly deals with the development of a defect classification system that uses Artificial Neural Network (ANN) to classify weld defects based on ultrasonic test data. The system enables real-time identification of weld defects which finds application in testing of critical welding applications and also reduces dependency on skilled workforce for the function. The study mainly consists of three parts- (i) Weld defect detection using Ultrasonic Testing (UT) (ii) Implementation of ANN (iii) Defect classification. An ultrasonic test performed on welded samples shows different results for welds with and without defects and further between defects as well. The ultrasonic test data is fed into the ANN algorithm to train it to identify the various weld defects. An Artificial Neural Network (ANN) is an information processing paradigm that uses a large number of highly interconnected processing elements called neurons, working in unison to solve the specific problems. There are two types of neural network architectures that are used for classification - a back propagation network (BPN) and a probabilistic neural network (PNN). Back propagation network has been used for the purpose of this study. In order to test the performance of the back propagation neural network, four classes of defect namely porosity, lack of side wall fusion, lack of penetration and slag inclusion are considered.

1. Introduction

Welding is a metal joining process wherein the metals are joined together by melting the base metals, fusion of the molten metals with the filler material, and finally cooling [1]. The properties of the fusion zone are largely determined by the properties of the material of the filler used and its fusibility with the base metal [2]. The welding process involves large amounts of heat energy and hence affects the areas surrounding the welded area (Heat Affected Zone). In this zone the microstructure and properties of the metal are altered by the weld, resulting in residual stresses, thus making it the weak link in the weld. In-service weld monitoring and defect classification systems usually inspect the fusion and heat-affected zones.

Welding defects are structural irregularities that occur in the welding process. It reduces the strength and usefulness of the weld. These defects have the potential to be dangerous as they might give rise to high stress intensities which may result in failure of the joint. Defects in welds must hence be identified and corrected. Correction may involve repair of the welded structure and change of process parameters to ensure defect-free welds for the rest of the batch.

Non-destructive testing (NDT) is a set of analysis techniques used to evaluate the properties of a material without alterations of the properties, structure or causing damage to the material. This set of techniques does not modify the characteristics of the component being inspected; hence proving to be a very crucial technique that can save both money and time in various aspects of product development and maintenance. Ultrasonic testing (UT) is a NDT technique that uses ultrasonic waves for finding defects in the components. It is a very versatile NDT method. Ultrasonic pulse-waves with central frequencies in the range of 0.1-15 MHz (sometimes higher values are also used), are used in the technique. Ultrasonic inspection has widespread applications – detection of flaws, dimensional measurement, characterization of material etc. The ultrasonic waves propagate through a medium at a known velocity. When these waves travel from one medium to another they are reflected back. This occurs when a defect occurs in an otherwise homogenous material. This is the basic principle behind detection of defects using Ultrasonic Testing, as shown in Figure 1.

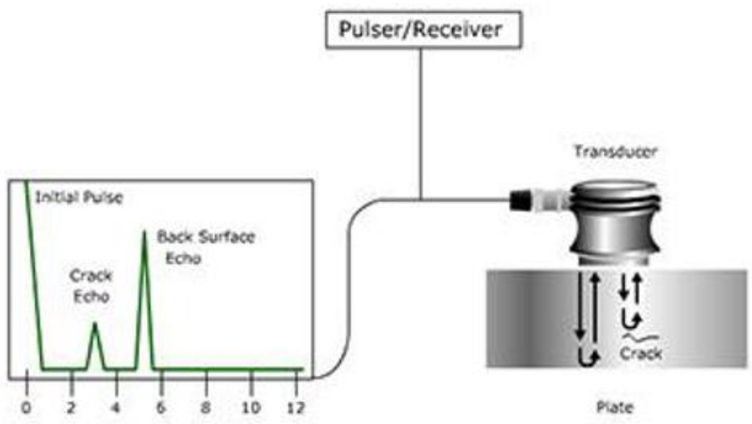

Figure 1. Principle of Ultrasonic Testing.

Weld monitoring will be employed in the case of critical welds that are required to withstand high stresses. It is done to check whether the welding parameters' values are being adhered to those specified in the welding manual. A defect classification system monitors and identifies defects in welds. An ultrasonic test performed on welded samples shows different results for welds with and without defects and further between defects as well. The data obtained from the test is fed into an algorithm to assist workers in determination of defects. Once the defect has been classified, it is possible for the operator to take necessary action to correct the flaw as well as the weld procedure or parameters for the rest of the lot. Quality control, prognostics, corrective maintenance, predictive maintenance and preventive maintenance are important aspects of improving efficiency of a process and hence result in an increase in profits.

Traditional defect identification and classification systems are based on observation and expertise of the worker. The ultrasonic data patterns for the different defect types are however similar and can be hard to interpret by mere observation. They can be inaccurate, time consuming and rely heavily on experience of the labour employed. Many attempts have been made to develop the automation of inspection process in the manufacturing field. This also led to automated systems for weld defect

classification.Automated techniques showed higher probability of detection in all situations and sizing errors were smaller for internal defects. Besides, automated tests reduced the time of inspection. [3]
Machine vision systems were developed to identify the defects of welded joints.Wang and Liao [4] describes the use of 12 numeric features to define each defect instance. The extracted feature values are then used to classify defects by using two popular algorithms: fuzzy KNN and MLP neural networks classifiers. Mirapeix et al. [5] describes a method that performs automatic weld defect detection and classification based on a combination of principal component analysis (PCA) and an Artificial Neural Network. Vilar et al. [6] describes an automatic detection system to recognize welding defects in radiographic images while he describes an adaptive-network-based fuzzy inference system to recognize welding defects in radiographic images in [7]. Masnata, et al. [8] proposed a methodology for the automatic recognition of weld defects, detected by a P-scan ultrasonic system, which has been developed within two stages in the present work.
Computerization of defect analysis in industrial inspection using neural networks reduces analysis time. Mechanization of vision inspection system eliminates the human error when the analysis is done by the inspector. Multiple views are successfully combined from information of two different points of view. It is a robust approach to flaw identification. Use of decision making algorithms overcome the difficulties faced in the conventional mode and considerably reduce the total cost.

2. Artificial Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that uses processing elements called neurons that work together to solve a given problem. The neurons are interdependent. An ANN is set up for a given application/problem, usually for recognizing a pattern or for classification of data. In this project, an ANN is used to classify data obtained from ultrasonic testing of welded joint, thereby functioning as a defect classification system. Neural networks replicate how the human brain actually functions. In pattern recognition applications, they are used as classifiers that check whether the input sample matches the input set used to train the ANN.

Artificial neurons make up the artificial neural network, the same way biological neurons make up the nervous system in a human body. An artificial neuron is a mathematical function that is analogous biological neurons present in the human body. The inputs that are provided to the artificial neurons can be considered analogous to the dendrites. The activation process is then carried out, which involves calculating a weighted sum of the inputs, and hence producing an output. The output can be considered analogous to a neuron’s axon. The weighted sum is passed through an activation function or transfer function. The transfer functions are predominantly non-linear. The transfer functions are usually monotonically increasing and bounded. They are also continuous and differentiable within their boundaries. [9-10]

3. Weld Defects

The defects under purview of this project are- lack of side wall fusion, lack of weld penetration, porosity of weld and slag inclusion. Each defect leads to variations in the output of ultrasonic test and this variation is used by the ANN system in defect classification.

3.1. Lack of sidewall fusion

When the weld does not fuse properly with the sidewall of the joint, fusion imperfections tend to occur. The principal causes of this defect are narrow preparation of joints, wrong parameter settings, magnetic arc blow, poor welder technique and improper cleaning of oily or scaled surfaces. These types of defects tend to occur when there is difficulty accessing the joint.

3.2. Lack of weld penetration

Lack of weld penetration is when the weld does not fuse properly in the root area. This defect can arise due to many reasons including using a thick root face, inadequate gap of root and applying low heat input.

3.3. Weld Porosity
When the weld metal solidifies, the various gases like nitrogen, oxygen and hydrogen that emerge from the molten weld area tend to be trapped inside the molten weld. This leads to the formation of cavities and the presence of these cavities is termed as porosity. This defect usually originates from poor gas shielding.

3.4. Slag Inclusion
Slag is basically small flux particles trapped in the weld. In the process of welding, when there is insufficient overlap, formations of voids take place. The slag becomes trapped in these voids with the deposition of the successive layer as the slag cannot be melted out. Entrapment of slag in cavities in the case of multi-pass welds is caused by too much undercut in the toe of the weld or the inconsistent contour of the weld passes. The extent and probability of occurrence of slag inclusion is mainly determined by the flux coating and the technique used by the welder.

4. Experimentation
An ultrasound transducer is connected to a machine that processes the signal and is passed over the component being inspected. The signal can either be received by reflection or attenuation. In reflection mode the sending and the receiving of the waves is done by the transducer. When the ultrasound wave reaches the back wall or an imperfection within the component, it is reflected back to the transducer. The machine that processes the input data, displays the output signal. The intensity of the reflection is represented by the amplitude of the output signal while the arrival time of the reflected signal is represented by the distance. In attenuation mode, the ultrasound is emitted by the transducer through the surface. The amount of sound reaching the other side, after passing through the medium, is detected by a receiver. The imperfections cause a reduction in the amount of sound being transmitted; hence the presence of defects can be detected.

The A-scan presentation displays the amount of received ultrasonic energy (y-axis) as a function of time (x-axis). Upon comparison of the signals obtained from the unknown reflector to that from a known reflector, we can estimate the relative size of discontinuity. The signal position on the horizontal sweep gives us the depth of the reflector. Hence A-Scan is used for defect classification systems.

The summary of sample data specifications is shown in Table 1. The samples used for this project are shown in Figure 2. The ultrasonic test data for each of the defects is represented in Figure 3.

Table 1. Summary of sample data

Title	Description
Number of Defects	4
Defects chosen	Lack of Sidewall fusion, lack of weld penetration, slag inclusion, porosity
Sample dimensions	300 mm x 300 mm x 20 mm
Number of samples	20
Number of trials	60
Number of data points studied	7200

Figure 2(a). Test sample for lack of sidewall fusion.

Figure 2(b). Test sample for lack of weld penetration.

Figure 2(c). Test Sample for weld porosity

Figure 2(d). Test sample for slag inclusion

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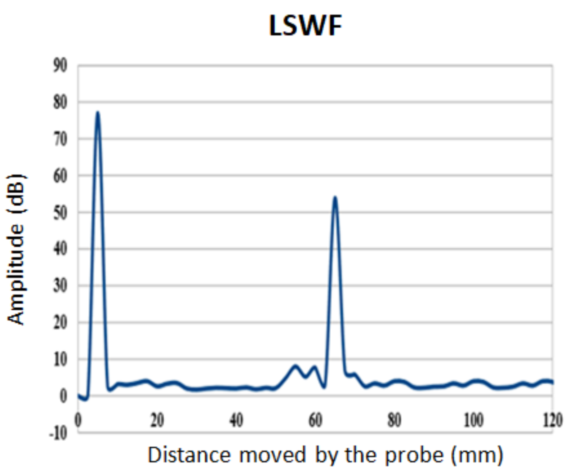

Figure 3(a). Defect pattern for lack of side wall fusion.

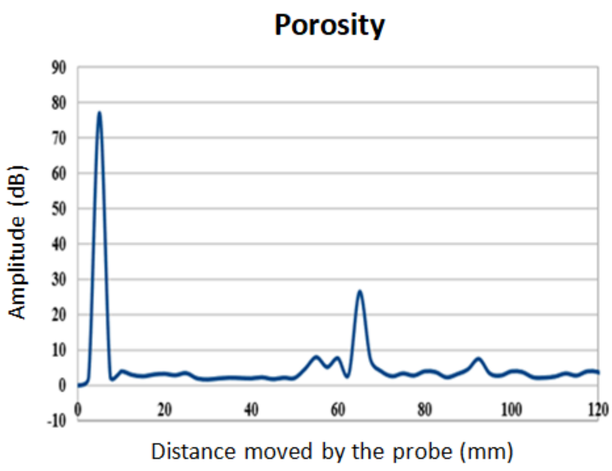

Figure 3(b). Defect pattern for porosity of weld.

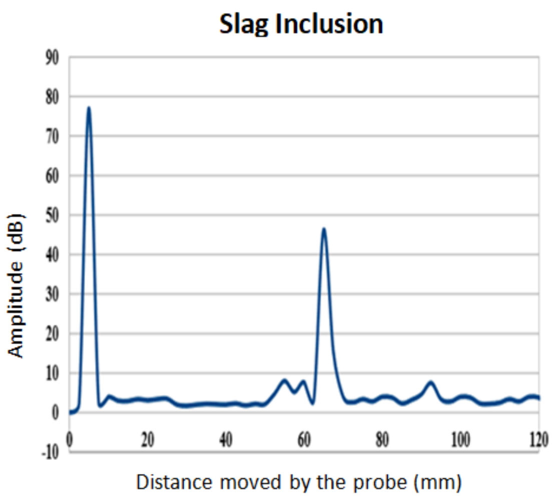

Figure 3(c). Defect pattern for lack of slag inclusion.

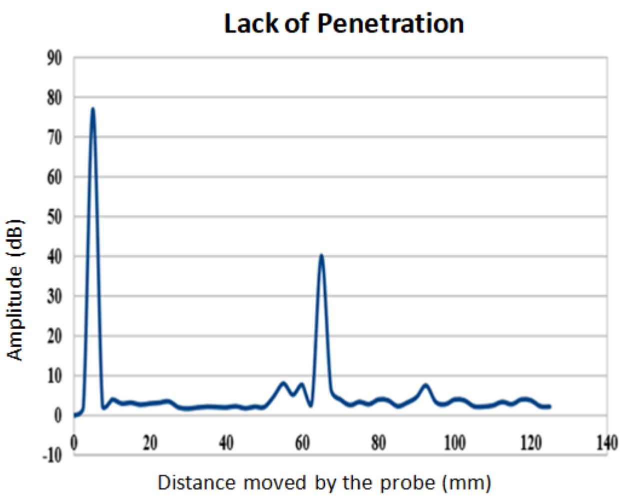

Figure 3(d). Defect pattern for lack of weld penetration.

5. Modelling

The Artificial Neural Networks takes the selected features, as inputs, for the classification of defects. For the purpose of classification, two types of ANN are usually preferred, namely back propagation network (BPN) and probabilistic neural network (PNN). BPN use both forward and backward propagation. In forward propagation, the output is calculated by taking a weighted sum of the input data. The weights are taken at random initially. In the case of back propagation, the error margin of the output is measured and the weights are adjusted accordingly to decrease this error margin. The forward and back propagation steps are repeated for the calibration of weights in order to predict the output accurately. Back propagation network has been used for the purpose of this project. The ANN framework is shown in Figure 3.

5.1. Back propagation networks

The algorithm repeats in a cycle consisting of the following processes: propagation and updating weights. When input data is provided to the network, forward propagation of the input takes place. The input passes through many layers by forward propagation and finally enters the output layer. A comparison is then made between the output and desired output. This is done using a loss function and separate values of errors are calculated for every neuron present in the output layer. Each neuron is then associated with a value, that approximately represents the effect of the neuron on the output, through back propagation.

The gradient of the loss function with respect to the weights in the network is calculated based on these error values, by back propagation. The optimization method takes in the gradient value and uses it for updating the weights. The optimization method aims at minimizing the loss function. With the training of the network, the neurons in the intermediate layers start to rearrange themselves in such a way that they learn to recognize various aspects of the input. After training, when an arbitrary input pattern that resembles a feature that the neurons have "learned" to recognize, is presented, an active output is given by the network; even if the input contains noise or is incomplete.

5.2. Learning methods

Supervised machine learning is the formulation of a function based on labelled training data. The training data consist of sample data whose characteristics are known. The desired output value and the corresponding input values are given. The training data is analyzed by the algorithm and a function is formulated. The algorithm is optimized to determine class labels for any inputs. The learning algorithm should be able to generalize from the training data to unseen situations in a "reasonable" way. Unsupervised machine learning is the formulation of a function based on unlabeled data.

Lawson et al. [11] described the application of image processing and neural networks (ANNs) in the complete automation of the decision-making process involved in the interpretation of TOFD scans. Local area analysis is utilised to derive a feature vector containing two-dimensional information on defect and non-defect areas. These vectors are then classified using an ANN trained with the back-propagation algorithm.

5.3. Learning algorithms

Selecting a model from the set of allowed models that minimizes the cost criterion is termed as training a neural network model. The training algorithms use various optimization methods and statistics. Gradient descent is used for ANN, and the gradients are computed using backpropagation.

There are generally four steps to perform the classification of data

1. Assemble the training data
2. Create the network object
3. Train the network
4. Simulate the network response to new inputs

5.4. Classification of Four Classes of Defects

A neural-fuzzy classifier combines the merits of both neural and fuzzy classifiers while overcoming their drawbacks and limitations. It is based on a three-layer feed-forward neural network. It shows great potential and exhibits high levels of accuracy, consistency and reliability, with low times for computation. [12]

Here, four classes of defects are considered in order to test the performance of the BPN. The implemented BPN structure for classification of four classes of defect is shown in Figure 4. The neurons, activation function, and training algorithm are varied. A fully connected feed-forward neural network is selected consisting of an input layer, an output layer and one hidden layer. An input layer has 1 input corresponding to amplitude and hidden layer consists of 7 neurons. The output layer has three neurons. In the output layer, 0 0 1 is set for lack of penetration, 0 1 0 for porosity, 0 1 1 for lack of sidewall fusion and 1 0 0 for slag inclusion. No defect class is represented by 0 0 0 and maximum amplitude is represented by 1 1 1. The back propagation 228 neural network architecture is 1-7-3.

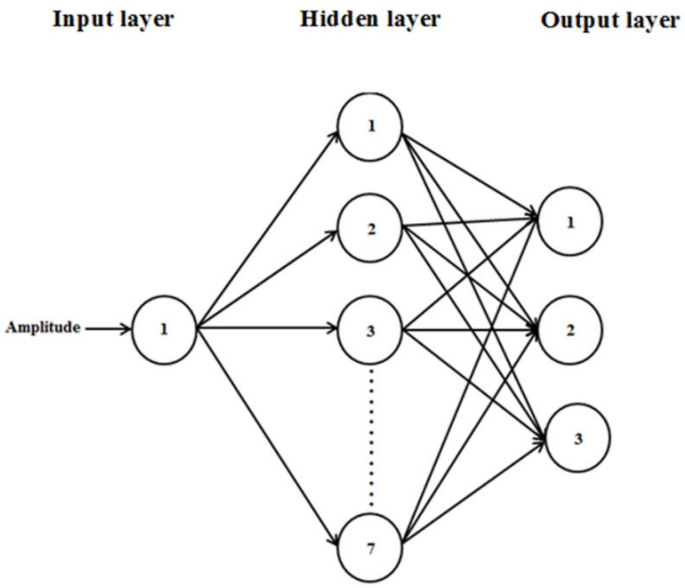

Figure 4. ANN Framework

6. Results and Discussion

The ultrasonic test data is fed into the ANN algorithm to train it to identify the various weld defects. The amplitude at different distances of 5 samples with reference defects is determined using ultrasonic testing. The graphical representation of the sample with defect is also given below.

6.1. Lack of side wall fusion

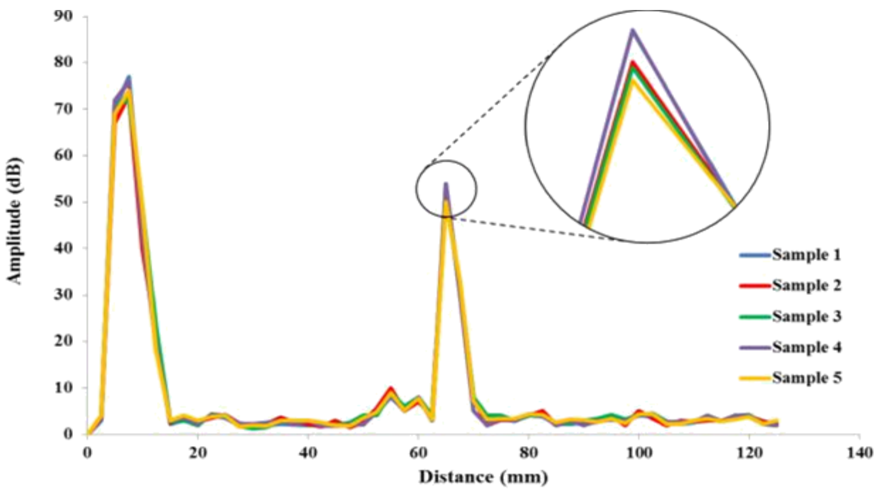

Figure 5. Test graph for lack of side wall fusion.

6.2. Porosity

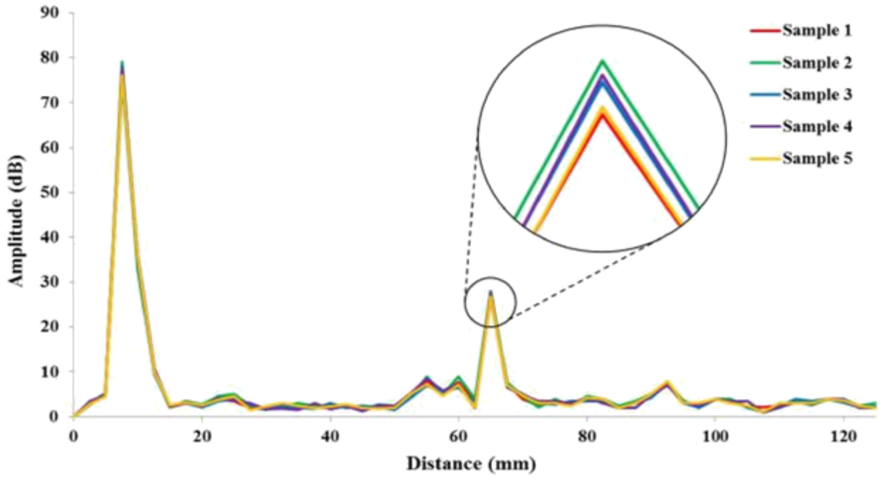

Figure 6. Test graph for porosity.

6.3. Lack of weld penetration

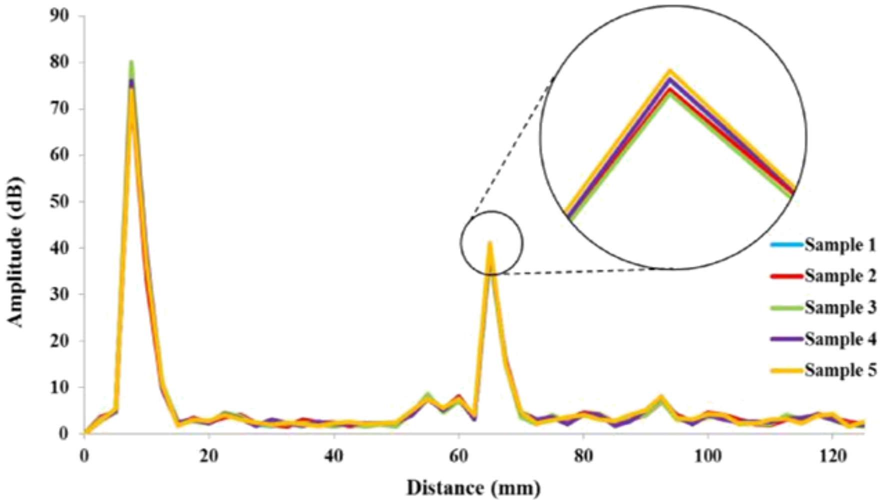

Figure 7. Test graph for weld penetration.

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6.4. Slag inclusion

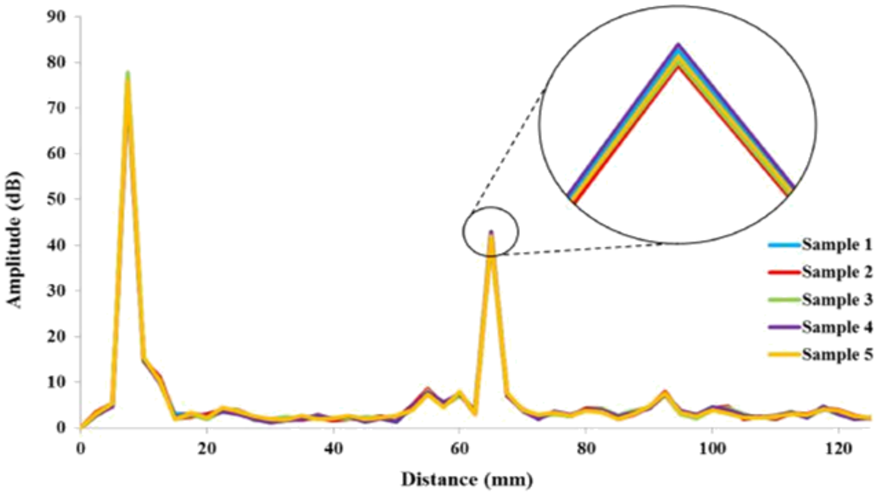

Figure 8. Test graph for lack of slag inclusion.

6.5. Comparison of defect data

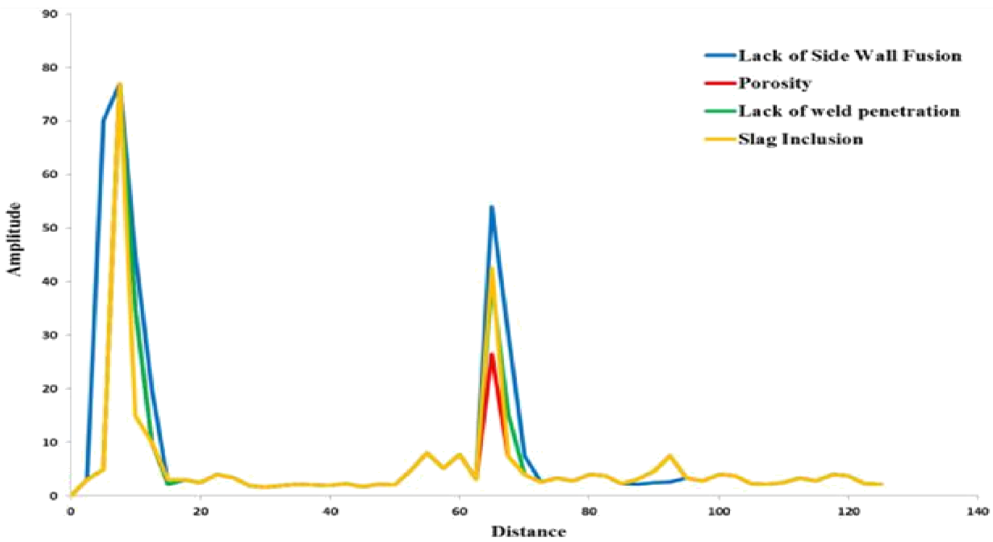

Figure 9. Consolidated test graph.

6.6. Testing

The ANN model is trained using the sample data from testing. Once trained, the ANN algorithm is fed with data of samples to be tested and the performance of model is evaluated. The curves corresponding to training, validation and testing are shown in Figure 9.

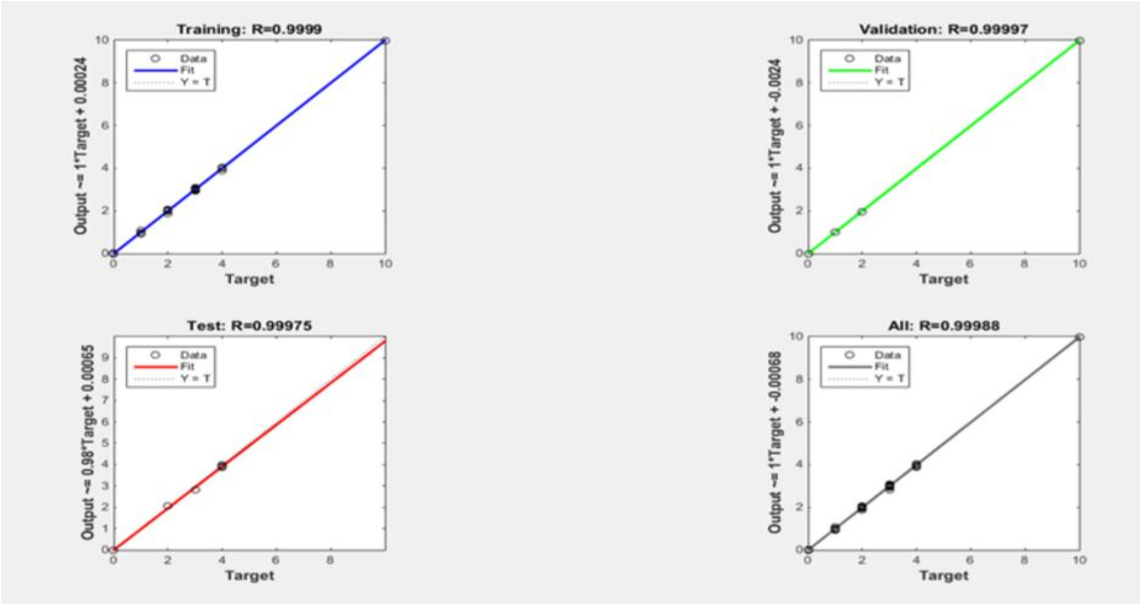

Figure 10. Training, validation and test graphs.

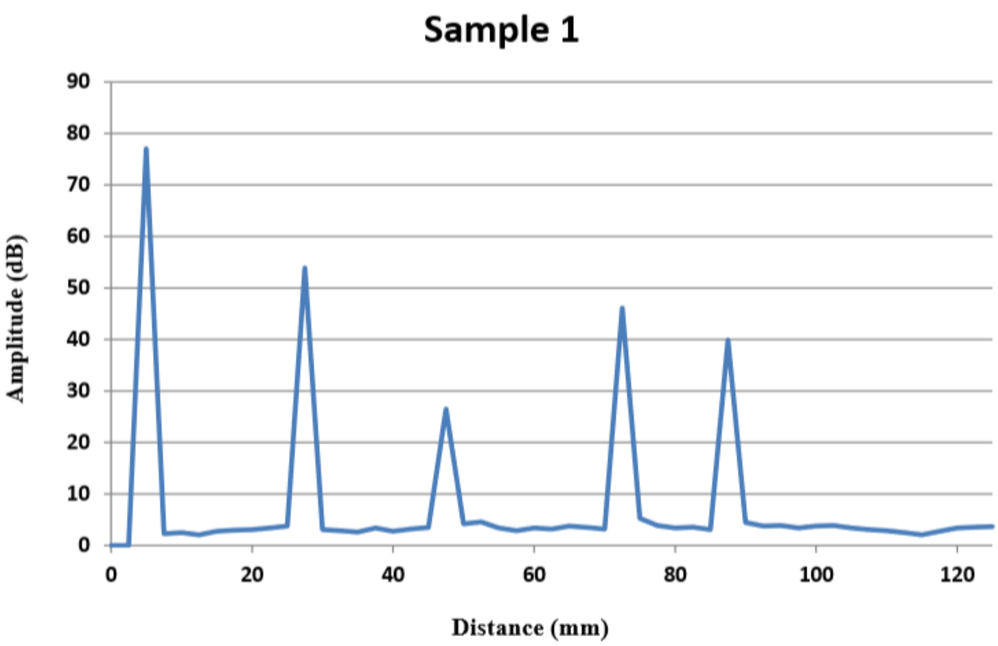

Figure 11. Test graph for sample 1.

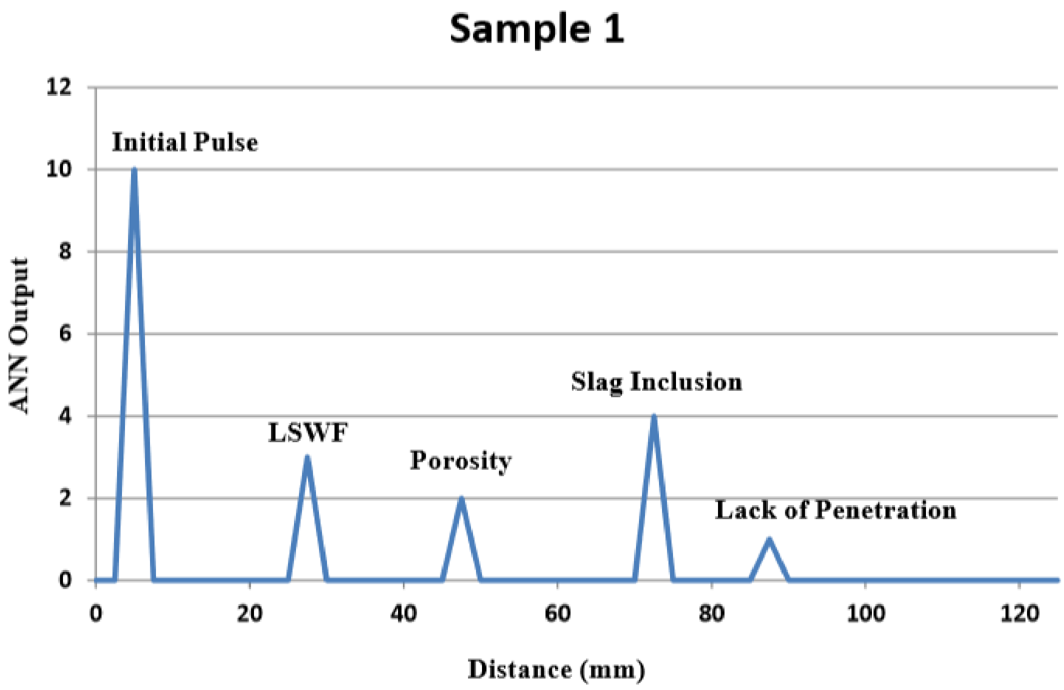

Figure 12. Output graph for Sample 1.

7. Conclusion

The ANN based system for weld defect classification was developed. The algorithm is capable of identifying four major weld defects, namely lack of side-wall fusion, lack of weld penetration, slag inclusion and weld porosity and the presence of no defect as well.

Standard samples were prepared containing the above defects and ultrasonic test data of these samples was fed to the system. This enabled training of the ANN framework.

The system is then tested using further sample data to ensure optimal functioning and the overall efficiency of classification is predicted. The efficiency of the system was found to be 91.7% using back-propagation network.

The efficiency is sufficiently high for the system to be implemented in large scale operations. This reduces the necessity for skilled labour required in testing applications and also improves process efficiency by reducing inspection time and hence lead time.

The system thus offers great potential for application in sectors with stringent weld requirements and can improve the profitability of such industries in terms of labour and time costs.

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