Optimization of parameters for the shot peening effect On Welded specimen using Artificial Neural Network

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Abstract

The welding process induces Residual tensile stress that is detrimental to Fatigue life. Tensile stress act to stretch or pull apart the surface of the material. With enough loads cycle at a high enough tensile stress, a metal surface initiate a crack. Significant improvement in Fatigue life can be obtained by modifying the Residual stress level in the material. The intent of this paper is for Butt welded similar and dissimilar joint, evaluate Residual stress level by using most accurate and best developed X-Ray diffraction method, before and after surface modification. In this paper, welding compressive residual stress can be modified by Shot peening, which required simple equipment and treatment is extensively employed as a method to improve Fatigue strength. This study uses MATLAB software to analyze two experimental data sets using a neural network fitting tool. According to the results, artificial neural networks (ANNs) are accurate and results show that ANN models can be used successfully for predicting surface roughness changes during shot Peening Process.

Keywords : Shot Peeening, Residual Stress, Fatigue strength, artificial neural networks

1. Introduction

Residual stress directly affects a components fatigue life. Detrimental residual tensile stress decreases the fatigue life while beneficial residual compressive stress increases the fatigue life. Both types will be thoroughly investigated through the use of X-ray diffraction in this paper. This paper will investigate how detrimental residual stresses are created through the welding process[1,2,3]. Shot peening is a cold working process used to increase the fatigue properties and hardness of metal components. During the peening process, the surface of the component is bombarded with small spherical media called shot. Overlapping dimples develop a uniform layer of residual compressive stress in the metal. It is well known that cracks will not develop in a compressively stressed zone. Since nearly all fatigue failures originate at the surface of a part, compressive stresses induced by shot peening provide considerable increase in part life. When controlled properly, all surface area, which is susceptible to fatigue crack initiation, is encapsulated in a uniform layer of high magnitude compressive stress[4,5].

It is seen that the hardness of material increases by means of shot peening operation. This means that when a welded component undergoes shot peening operation the residual tensile stress in the specimen reduces and compressive stress induced. The residual tensile stress reduces the hardness of material and material with high compressive stress has high hardness.

Welding induces Residual tensile stress which decreases the Fatigue life of component. This Residual stress is measured by X-Ray diffraction method. X-ray residual stress measurement is considered as a nondestructive method. As the Residual tensile stress decreases the Fatigue life, Residual stress modification such as Shot peening is used. Shot peening is a cold work process used to finish metal parts to prevent fatigue and stress corrosion failures and increase product life for the part. In shot peening, small spherical shot bombards the surface of the part to be finished. The shot acts like a peen hammer, dimpling the surface and causing compression stresses under the dimple.

2. Methodology

Brief description of the methodology followed during the course of this study is as follows;

a) Carry out the Literature regarding the fatigue life of welded joint and on surface enhancement treatment by referring journals, books and related documents.
b) Carry out the Experimental investigation of induced residual stress in butt welded joint before and after surface modification process by non-destructive technique of x-ray diffraction method.
c) Carry out the surface modification of butt welded specimen by Shot peening method.
d) Carry out the estimation of the fatigue life of butt welded joint before and after surface Shot peening process with the help of MTS uniaxial testing machine.
e) To analyze the effect of RS modification of welded component on fatigue life by comparing the fatigue life of component before and after shot peening.

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Material selection is a process which is performed to select the best materials which may have the potential to perform well both in industrially and commercially. Today selection of materials is an important part of industrial designs because the competition in the market is heavy. Failures arising from bad material selection are not uncommon in many industries. In an application that demands a high tensile strength, a material with higher tensile strength must be selected. If a proper material selection is not done, the product life tends to be highly unpredictable. Otherwise, the result it is highly susceptible for failures. In the selection process, materials will be assessed for tensile strength and modulus, flexural strength and modulus, impact strength, compressive strength, fatigue endurance, creep, and stress-relaxation properties depending on the application. This will ensure that the design will have a better probability of succeeding. It will also assure that the design is technically fit to obtain desired properties.

3. **Experimentation Details**

3.1. Specimen preparation

In this work, a mild steel plate and stainless steel plate of thickness 4 mm is used. Dumbbell specimens were prepared with ASTM (American Society for Testing and Materials) E647 and BS 7608 (British Standard 7608) specifications. Two plates of size 110x20 mm is taken for welding & single V-joint with bevel angle 35 degrees, root face 3 mm are prepared. The plate is butt-welded by shielded metal arc welding process with E-6013 electrode. Butt weld joint is prepared with good surface finishing conditions and with an electrode specification E-6013. Then milling of the plates as per specimen diagram is given below. Fig 1 explains the geometry details of Dumbbell Specimen for Experimental Testing.

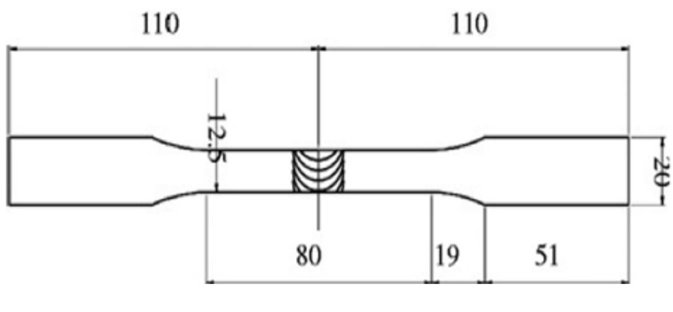

Fig 1 Dumbbell Specimen prepared for experimental testing

(All dimensions in mm)

3.2. Shot Peening

Shot peening is a cold work process used to finish metal parts to prevent fatigue and stress corrosion failures and increase product life for the part. It requires simple equipment and treatment, is extensively employed as a method to improve fatigue life and hardness of material. In shot peening, small spherical shot bombards the surface of the part to be finished. The shot acts like a peen hammer, dimpling the surface and causing compression stresses under the dimple.

In order to perform Shot peening on the material we first need to be calculating the intensity by which the shot ball made to be strike on the material for a calculated time. In this project work, to find the intensity several pieces of Almen strips is used as shown in Fig. 2. Each Almen strips is first placed on the bending measure equipment which shows zero reading that means there is no bending on the strips. Strips is now placed inside the Wheel blasting type of Shot peening machine and cast steel Shot ball (S330 type) of diameter ranging from 0.7 to 1.20 mm is made to strike with velocity of 47 m/sec at an angle of 45 ˚ on the strips for a particular time period. Strips are now taken out and its bending is measured. Which gives the some value and this indicates there is some bending occurs after shot peening.

Fig 2 Specimens before Shot peening

3.3 Prediction of Impact of shot peening on Surface Hardness by Artificial Neural Network Models

The prediction or estimation of data based on statistical methods learned from specific patterns in the dataset represents the primary function of ANN. It is a machine learning concept with large datasets for training the system and making the system capable of predicting the output. ANN is an alternative approach to experimental and physical models for prediction and simulation of behaviour. ANN handles nonlinear, irregular data sets, and patterns, accepts numerous variables, and provides acceptable general solutions.

3.3.1 Design and development of Artificial Neural Network for predicting Surface roughness

In this work, the parameters controlling the surface roughness behaviour of the Ti-6Al-4V are numerous. The maximum amount of data that can be generated so that an accurate prediction will be possible was obtained through laboratory tests. The major contributing factors for surface roughness behaviour are burnishing speed, burnishing passes, and burnishing pressure. For surface roughness analysis, data from surface roughness tests carried out by ZEISS smart proof 5 has been taken [6,7, 8, 9]. The software used is MATLAB R2015a. In this software, a neural network fitting tool is used in which burnishing speed, burnishing passes, and burnishing pressure are taken as inputs and measured surface roughness values are taken as outputs. The choice of transfer function, hidden units, numbers of neurons, and layer arrangement are all taken into account in optimal model design. The best ANN model was created by using a trial-and-error approach. The comparison of the system's anticipated performance converges, assuming an effective ANN model, towards zero error [10,11,12,13]. Two algorithms are chosen for the current work based on the literature: 1. Levenberg Marquardt Bayesian Regularization is second. For the network models, the equivalent transfer functions are Trainlm and Trainbr. Table 1 displays the input parameters utilised in this ANN prediction.

Table 1 Input parameters for ANN prediction

Sl No	Input variables	Outcome
1	Number of burnishing Passes	Surface Roughness (μm)
2	LPB Burnishing Pressure (MPa)	
3	Burnishing Speed (mm/min)	

These algorithms are capable of computing the nonlinear behaviour of the composite wear behaviour. Also, relatively large data sets are handled by the algorithms. The sigmoid transfer functions used in ANN are also used to account for nonlinear behaviour.

Entities and components of the ANN structure is indicated in Table 2. Artificial neural networks are made up of neurons, which are basic computational components placed in the network's several layers: an input layer, hidden layers, and an output layer. The artificial neural network was trained and tested using the Levenberg-Marquardt (LM) backpropagation approach in the MATLAB neural network module.

Table 2 Entities and Components of ANN structure

Particular	ANN Parameters	Remarks
Training Algorithm	Levenberg-Marquardt Sealed Conjugate Gradient Conjugate Gradient with Powell	Nonlinear, medium Data set
Network Configuration	3-10-1	Input layer-3 Hidden layer-10 Output layer-1
Transfer function	Trainlm, Traincgb, Trainscg	Commonly used for Prediction
Performance function	MSE	Best Error function

Levenberg-Marquardt's method approaches full training levels without the need to compute second derivatives.The Levenberg-Marquardt formulation factors were shown to be faster than other existing techniques, but required more memory to achieve the same error bound convergence. The methodology used in this work, to predict surface roughness using ANN, ANN structure, and ANN Model is shown in **Fig** 4. Each neuron's input p is multiplied by correctly assigned weights w, which define the model's fitting parameters. The linear basis function is used to sum the weighted inputs (equation1). To create the input to the transfer function f, the total is multiplied by a bias factor. Neurons can create their output using any differentiable transfer function f. This can be summed up in the following formula:

$$a = \sum_{i=0}^{n} (W_i p_i + b) \text{ ------------}\mathbf{1}$$

Usually employed as an activation function, the "sigmoid function" This function generates a value between 0 and 1 for each provided value. Eq contributes as its defining feature (2)

$$\boldsymbol{f} = \frac{1}{(1+e^{-a})} \text{------------}\mathbf{2}$$

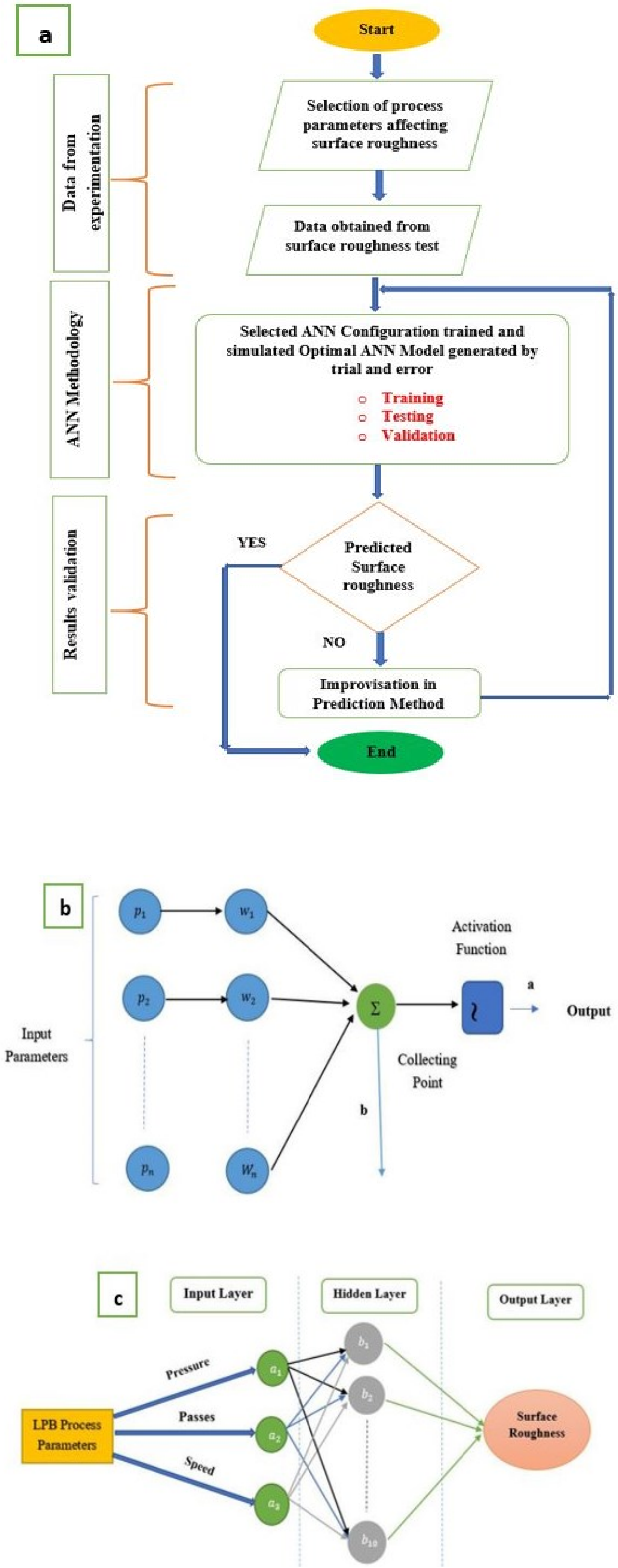

Fig 3 (a) Proposed procedure for ANN-based surface roughness prediction (b) Model of Neuron (c) ANN Structure

The effectiveness of the ANN estimate model was assessed by using the mean square error (MSE). The MSE is the average of the squares of "error." Equation (Eq.) determines it (6).

$$MSE = \frac{1}{N}\sum_{i=1}^{N} \quad (t_i - a_i)^2 \text{------------}\mathbf{3}$$

where t_i denotes the 'i'th ANN output data; a_i denotes the 'i'th experimental output data; N denotes the N^{th} number of dataset. Schematic illustartion of ANN model configuration used in this work, consists of 3 inputs and 1 output is shown in the Fig 5.

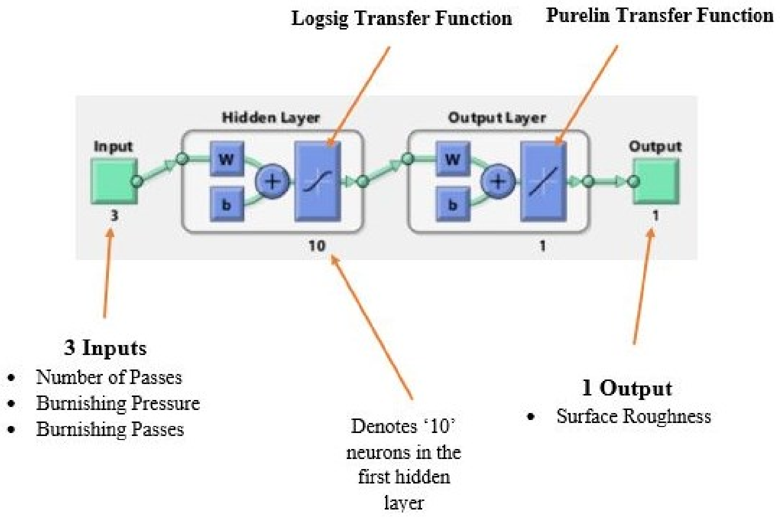

Fig 4 Selected ANN Model Configuration

4 Results, Conclusions and Scope for Future Work

In this chapter the results obtained from basic experimental tests namely shot peening, Rockwell hardness test, residual stress measurement test, fatigue test on all the considered specimens are tabulated, compared and discussed carefully in the following sections.

4.1. Results

In this section the results obtained from various experimental tests are tabulated. The residual stress value, hardness, fatigue life and microstructure of two given specimens before and after shot peening process are tabulated and compared as follows.

4.2 Comparison of experimental and ANN surface roughness results

By selecting between 30% and 40% of the available data at random, an ANN technique was used to generate a training set from the experimental training dataset. To make sure that the estimates were precise, the remaining 60 to 70 percent of the data were employed as a testing set.Random sampling was used to choose the training and test set. In order to evaluate the effectiveness of neural networks, the cross-validation approach used a small portion (20%) of the training set as a validation set. The mean square error (MSE) was used to gauge how well the ANN estimating model performed[14, 15].

Fig. 6 shows that after three iterations, the least mean square error relying on ANN iterations converged (epochs). The matching R2 values for the training, validation, and testing data sets for the prediction of the surface roughness by ANN were 0.99,0.96, and 0.95 respectively, as shown in Fig. 4. (b) 0. 0.98122 was found to be the entire R2 value. The model performs better in the prediction of the surface roughness of burnished specimens for random data sets because the cumulative R value is near to unity.Table 4.7 shows a comparison of experimental surface roughness findings with ANN predicted values

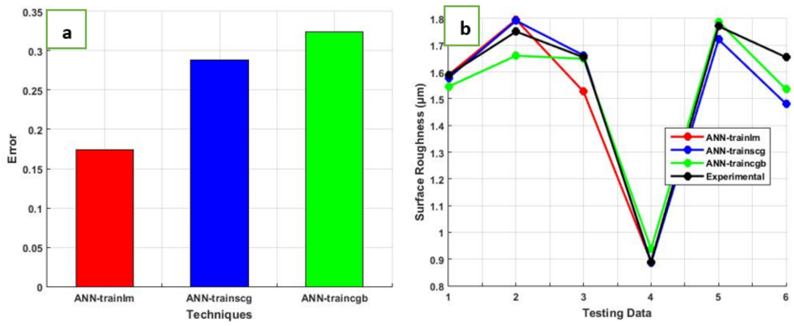

Fig 5 a) Error obtained from 3 different ANN techniques. b) convergence of surface roughness obtained from 3 different ANN techniques

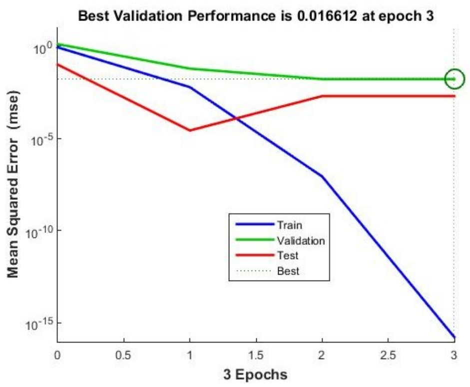

Fig 6 Mean square error graph

$$\text{Relative error} = \frac{PV - MV}{MV} \times 100 \text{------}\mathbf{4}$$

Table 4-7 Comparison of ANN results with experimentation results

			Surface Roughness (µm)	

Number of Passes	Shot Peening Pressure (MPa)	Shot Peening Speed (mm/min)	Experimental Results	ANN Predictions	Relative Error (%)
2	15	500	0.79	0.81	2.531646
2	10	700	0.8105	0.98	20.91302
2	20	300	0.8139	0.988	21.39083
1	15	500	0.8325	0.97	16.51652
1	10	700	0.8365	0.93	11.17753
1	20	300	1.037	1.15	10.89682
3	15	500	1.438	1.58	9.874826
3	10	700	1.589	1.5779	0.69855
3	20	300	1.751	1.79	2.227299
1	10	300	1.655	1.5261	7.78852
2	15	300	0.89	0.88	1.1236
3	20	500	1.771	1.71	3.44438
1	15	300	1.655	1.63	1.51057

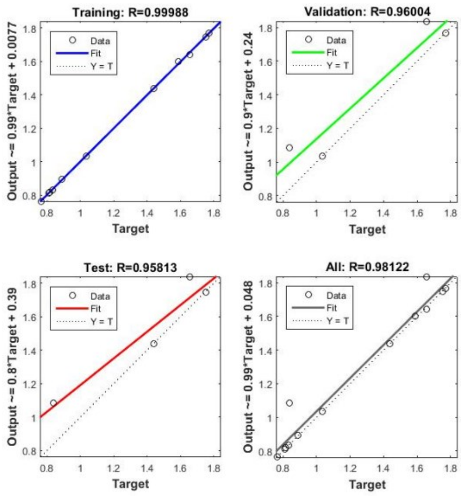

Fig 7 Surface roughness under experimental and predicted conditions

4.3. Conclusions

Conclusions are drawn based on the results obtained from experimental methods are summarized as follows:-

1. The welding processes create residual tensile stresses; which is detrimental to fatigue life these stresses can be reduced through shot peening process.

2. With the shot peening treatment the welded joint fatigue strength is significantly improved.

3. The current research is an attempt to see if the ANN technique might be used to predict surface roughness. As a result of this study, it was observed that the designed ANN model was capable of accurately predicting surface roughness. Because the gathered results are near to experimental data, trained ANN can anticipate intermediate results that were not attained in the experiment.

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