Prediction and Control of Residual Stress Distribution in Welded Joint Using Artificial Neural Network

Harish[1], D. Shivalingappa[1], Roopa G[2]

[1]Department of Mechanical Engineering, B. N. M. Institute of Technology, Bengaluru 560070, India.

[2]Department of Mathematics, B. N. M. Institute of Technology, Bengaluru 560070, India.

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 Project is an artificial neural network approach was used to predict the residual stresses in welded joint. MATLAB was used to train the neural network using the Levenberg-Marquardt technique. The correlation results between experimental data and ANN outputs confirmed the feasibility of using artificial neural networks for modelling and predicting the residual streses.

Keywords : Residual stress, Hardness, welded joint, ANN

corresponding author e-mail address: harishbba@gmail.com

1. Introduction

Welding process induces residual stress that is detrimental to fatigue life. Tensile residual stress act to stretch or pull apart the surface of the material. With enough load cycles and high enough tensile stress, a metal surface will initiate crack. It is well known that when a component fails in fatigue, the failure location is usually the welded zone. Residual stress directly affects a components fatigue life. The shot acts like a peen hammer, dimpling the surface and causing compression stresses under the dimple.

Mark S. Molzen et al. [1] studied about the welding process which induces residual tensile stress that is detrimental to fatigue life. Tensile stresses act to stretch or pull apart the surface of the material. Significant improvements in fatigue life can be obtained by modifying the residual stress levels in the material. Two methods of performing these are through heat treating and shot peening. Sylvain Chataingner et al. [2] investigated about the steel structures which are mainly prone to two types of degradation: corrosion and fatigue particularly in the case of welded structures. The presented work aims at investigating two treatment methods to increase the fatigue life expectancy of welded steel joints. It includes both numerical and experimental investigations and is interested in the use of shot peening. M Hasegawa et al. [3] investigated about the shot peening method, which requires simple equipment and treatment, is extensively employed as a method to improve fatigue strength and to reduce the tensile stress in the component.

Manoj Saini et al. [4] studied the role of dissimilar metal joints between austenitic stainless steels and carbon steels containing low amounts of carbon are being extensively utilized in many high-temperature applications in energy conversion systems. In steam generating power stations, the parts of boilers that are subjected to lower temperatures as in the primary boiler tubes and heat exchangers are made of ferritic steel(mild steel) for economic reasons.

Xiaohua Cheng et al. [5] addressed the issue of high tensile weld residual stress is one important factor contributing to fatigue crack development even under reversal or compressive cyclic loadings. A compressive stress induced by post-weld treatment is beneficial by eliminating the tensile residual stresses and generating compressive residual stresses, which improves fatigue strength of welded structures.

M.H. (Johnny) Johnson. [6] Investigated about the most industrial machines and the structures that support them are subjected to fluctuating loads over their lifetimes, even if nothing more than the cyclic loading associated with starting and stopping.

Vinod M. Bansode et al. [7] investigated about the failure analysis based on stress life approach may be useful for predicting the life time of weld in the structure. This study presents an upcoming methodology in new three dimensionals Finite Element Model to calculate the fatigue life of weld. Ansys 12.1 simulation software uses stress-lifemethod, based on a static non-linear Structural analysis. The weld material

2

S-N curves were experimentally determined by the Fatigue testing of the dumbbell specimen as per 7608 standard.

Baptista R. et al. [8] investigated about the fatigue behavior in terms of environment (air and 3% NaCl) and weld toe treatment (as welded, toe grinding, PPAW Dressing and Hammer Peening). Fatigue life improvement techniques are very important today, because it is imperative to increase the fatigue life of welded structures, while decreasing the global cost of producing maintaining them. Fatigue life improvement techniques rely on extending the initiation phase, by reducing the severity of the weld toe details or introducing a compressive residual stress field [5]. Improvement techniques also reduce the crack propagation speed; which increases the total fatigue life of the structure.

B. Mvola et al. [9] studied about the dissimilar metals welding. The construction industry has for many years shown interest in opportunities offered by the welding of dissimilar metals. The need for appropriate and effective techniques has increased in recent decades with efforts to meet wide disparities constraints in services

N. S. Rossini et al. [10] studied about the methods of measuring Residual stresses in Components. Residual stresses can be defined as the stresses that remain within a material or body after manufacture and material processing in the absence of external forces or thermal gradients. Rafailov G et al. [11] investigated about the prediction and XRD measuring of residual stress in machined welded parts. Residual stress distribution was measured in a spot welded disk before and after machining of the welded zone. The measurements were done using both X-Ray diffraction and Hole-Drilling (HD) methods. A numerical simulation of the distribution of residual stress was applied in order to predict the behavior of the stress. The distributions obtained by X-Ray diffraction, Hole-Drilling, and the numerical simulation were alike, and they were similar to the distribution expected according to the literature, i.e. high tensile stress near the fusion zone, which drops sharply to compressive stress when moving farther away from it, and then rises moderately towards zero at the edge of the disk. Y. Kudryavtsev et al. [12] investigated about the fatigue life of welded Elements, Residual Stresses and Improvement Treatments. Residual stresses (RS) can significantly affect engineering properties of materials and structural components, notably fatigue life, distortion, dimensional stability, corrosion

3

resistance. RS play an exceptionally significant role in fatigue of welded elements. The influence of RS on the multi-cycle fatigue life of butt and fillet welds can be compared with the effects of stress concentration. Even more significant are the effects of RS on the fatigue life of welded elements in the case of relieving harmful tensile RS and introducing beneficial compressive RS in the weld toe zones. The results of fatigue testing of welded specimens in as-welded condition and after application of ultrasonic peening showed that in case of non-load caring fillet welded joint in high strength steel, the redistribution of RS resulted in approximately two-fold increase in the limit stress range.

The most common definition of ANN is a mathematical model influenced by biology that is used to address challenging scientific and technical issues. To replicate synaptic connection strength in biological neurones, artificial neurones use weightings or multiplication factors. The operation of the hillock zone is modelled using summations of signals received from each connection [13, 14,15,16].

2. Methodology

The above defined objectives were accomplished by adopting a methodology for Experimental analysis. Brief description of the methodology followed during the courseof 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) The surface residual stress was predicted for the specified process parameters using artificial neural network models. The ANN configuration was trained using data from an experimental set of shot peening pressure. The results of the ANN model were compared with the results obtained from experimentation.

3. Design and development of Artificial Neural Network for predicting Residual stress

In this work, the parameters controlling the Residual stress behaviour of the SS316l 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 shot peening pressure, Impact angle. For Residual stress analysis, data from residual stress tests carried out by PANalytical Empyrean X-ray diffractometer has been taken. The software used is MATLAB R2015a. In this software, a neural network fitting tool is used in which shot peening pressure, impact angle are taken as inputs and measured Residual stress values are taken as outputs. Table 1 displays the input parameters utilised in this ANN prediction.

Table 1 Input parameters for ANN prediction

Sl No	Input variables	Outcome
1	Impact angle	Residual stress
2	shot peening pressure	

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. 1**.

The linear basis function is used to sum the weighted inputs (equation 7). 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 :

$$\boldsymbol{a} = \sum_{i=0}^{n} (\boldsymbol{W}_i \boldsymbol{p}_i + \boldsymbol{b}) \text{ ------------(1)}$$

Usually employed as an activation function, the "sigmoid function" This function generates a value between 0 and 1 for each provided value.

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

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 (9).

$$\boldsymbol{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\boldsymbol{t}_i - \boldsymbol{a}_i)^2 \text{------------(3)}$$

5

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. 2**

4. Results and Discussion

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.

Fig. 1 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. 2**.

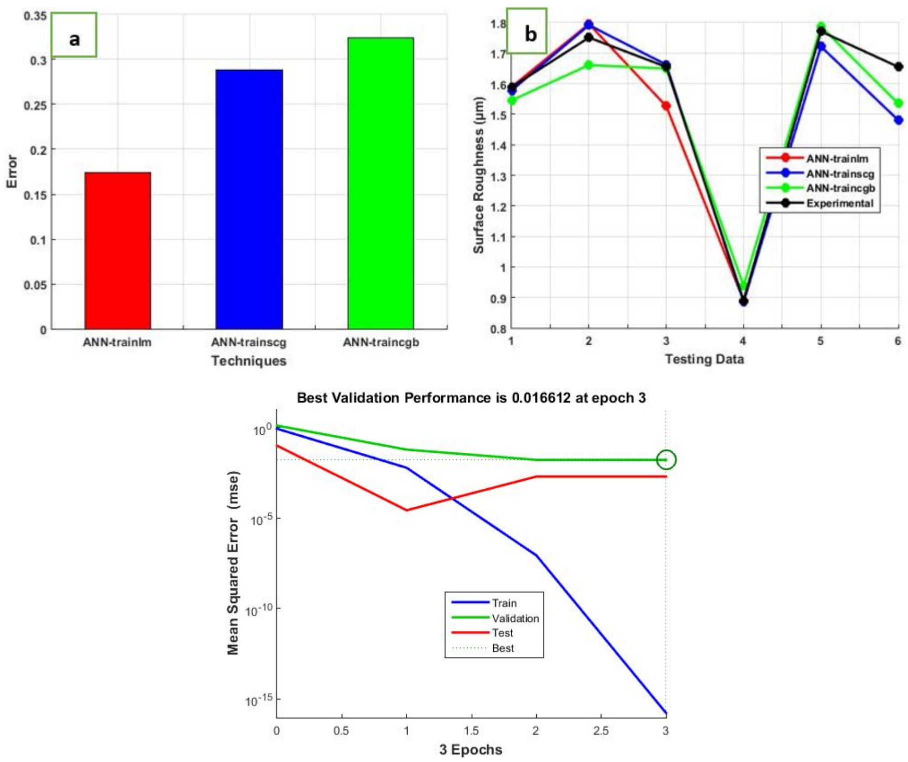

Fig. 1 a) Error obtained from 3 different ANN techniques. b) convergence of surface roughness obtained from 3 different ANN techniques and Mean square error graph

6

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 2** shows a comparison of experimental surface roughness findings with ANN predicted values.

Table 2 Comparison of ANN results with experimentation results

Shot Peening Pressure (MPa)	Impact angle	Residual Stress (MPa) Experimental Results	ANN Predictions	Relative Error (%)
5	0	-105	-115	2.531646
10	10	-107	-117	2.91302
15	20	-108.5	-118.5	2.39083
20	30	-110.33	-116.3	1.51652
25	40	-132	-142	1.17753
30	0	-143	-153	1.89682
35	10	-155	-159	9.874826
40	20	-165	-171	0.69855
45	30	-173	-179	2.227299
50	40	-183	-191	7.78852
55	0	-191	-198	1.1236
60	10	-193	-199	3.44438
65	20	-201	-210	1.51057

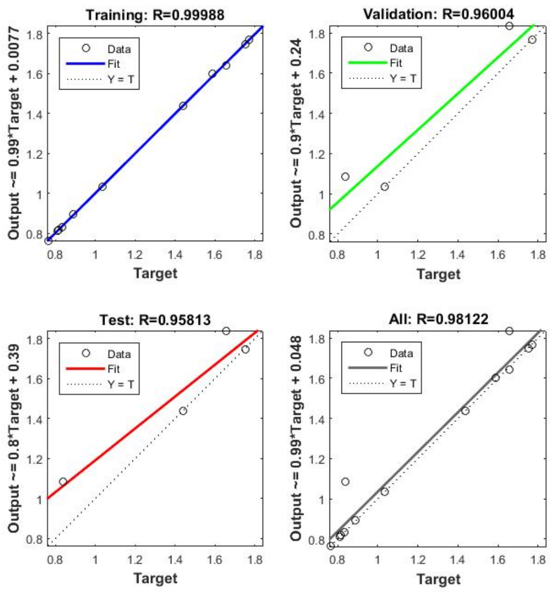

Fig. 2 Surface roughness under experimental and predicted conditions

7

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

5. Conclusions

The current research is an attempt to see if the ANN technique might be used to surface residual stress. As a result of this study, it was observed that the designed ANN model was capable of accurately predicting surface Residual stress. The maximum deviation is found to be 7.78%.

Because the gathered results are near to experimental data, trained ANN can anticipate intermediate results that were not attained in the experiment.

Surface residual stress (Ra), which is frequently used to monitor Fatigue strength, was taken into consideration as the performance metric in the current study. The architecture with three neurons in the input layer, two hidden layers with eight neurons each, and one neuron in the output layer (3-8-9-1) was found to have the lowest MSE value of 0.006 at 100000 cycles out of the 50 configurations that were utilized for training. As performance measures, coefficient of determination and standard error were selected to assess how well the models could predict surface residual stress. The coefficient of determination is a metric used in model analysis to assess how well a model predicts the results.

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9

10