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Prediction of tensile strength in friction stir welded aluminium alloy using artificial neural network

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Abstract

This paper presents a systematic approach to optimizing friction stir welding process parameters for the aluminium alloy. Friction stir welding (FSW) is solid state joining process widely used for the difficult welding joints of aluminum alloys. Weld quality is predominantly affected by welding input parameters. The welding parameters such as tool shoulder diameter, tool rotational speed, welding speed and axial force play a major role in deciding the joint strength. In present work an attempt has been made to join the aluminium alloy AA8014 by FSW using the conventional milling machine. Friction stir welding have been carried out on the 4 mm thick AA8014 plate. ANN has been developed based on back propagation (BP) of error for prediction of the tensile strength in FSW. The input parameters of the model consist of tool shoulder diameter, tool rotational speed, welding speed and axial force whereas the output of the model is the tensile strength of joint. The ANN was subsequently trained with experimental data. Testing of the ANN is carried out using experimental data not used during training. The results showed that the outcomes of the ANN are in good agreement with the experimental data; this indicates that the developed neural network can be used as an alternative way for calculating tensile strength for given process parameters.
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*Keywords :*Friction Stir Welding; Aluminium Alloy; Tensile Test; ANN

1. Introduction

Aluminium is the most widely used non-ferrous metal in the modern world. Many fusion welding process, such as metal inert gas welding (MIG), tungsten inert gas welding (TIG), electron beam welding (EBW) and laser beam welding (LBW) that are routinely used for joining aluminium alloys. Friction stir welding (FSW) is an solid state

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joining process in which the material that is being welded does not melt and recast. The Welding Institute (TWI), UK invented FSW process in 1991. Using this process, materials which previously thought to be difficult to weld because of melting related defect, can be weld very easily. FSW process is observed to offer several advantages over fusion welding [1]. The non consumable rotation tool creates the defect-free friction stir processed (FSP) regions by the material flow and friction heating [2]. However, the material flow behaviour is predominantly influenced by the FSW tool geometry and process parameters. Rajakumar et al. [3] studied the effect of rotational speed, welding speed, axial force, shoulder diameter, pin diameter and tool hardness on the strength properties of AA7075-T6 aluminium alloy. Cavaliere et al. [4] studied the effect of processing parameters on mechanical and microstructural properties of AA 6082 joints produced by friction stir welding. Okuyucu et al.[6] have used artificial neural network (ANN) to obtain correlation between FSW parameters and mechanical properties of aluminium plates. Many researchers have investigated the effect of the various welding process parameters on the strength properties of friction stir welded joint using various materials [2-9]. Different researchers have made attempts to optimize parameters of friction stir welding from time to time using different optimization models and solution techniques. In present study an attempt has been made to predict the tensile strength in FSW using ANN.

2. Experimentation

Conventional milling machine (BFW make, universal knee type) with appropriate fixture developed for FSW has been utilized for present experimental investigations. The chemical composition and mechanical properties of base metal are presented in Table 1 and 2 respectively. Non-consumable tool, made of high carbon, high chromium steel, H-13 has been used to fabricate the joints. The rolled plates of 4 mm thickness, AA8014 aluminium alloy, have been cut into the required size (300 mm x 150 mm) by power hacksaw. Square butt joint configuration (300 mm x 300 mm) has been prepared to fabricate FSW joints. The initial joint configuration is obtained by securing the plates in position using mechanical clamps. The direction of welding has been normal to the rolling direction. Single pass welding procedure has been followed to fabricate the joints. From the literature review the predominant factors which are having greater influence on tensile strength of friction stir welded aluminium alloys are identified. They are; tool shoulder diameter, rotational speed, welding speed and axial force. Trial experiments have been conducted to determine the working range of the parameters. Feasible limits of the parameters have been chosen in such a way that the friction stir welded joints should be free from any visible external defects. Total 25 experiments are carried out as shown in the table 3. The welded joints have been sliced using a power hacksaw and then machined to the required dimensions. Three tensile specimens have been prepared for each experiment as per the ASTM E8M-04 standard. Tensile strength of the FSW joints have been measured by conducting test on universal testing machine and the average of 3 results is presented in table 3.

Table 1: Chemical composition of AA8014 aluminium alloy

Fe	Cu	Ti	Mg	Mn	Si	Zn	Al
1.123	0.153	0.033	0.125	0.177	0.416	0.304	97.6

Table 2: Properties of AA8014 aluminium alloy

Tensile Strength Mpa	Density Kg/m^3	Thermal Conductivity W/mk	Melting Point ºC	Hardness HRB
152	2660	120	590	68

Table 3: Experiments and results

Experiment No.	Tool Shoulder Dia. mm	Rotational Speed rpm	Welding Speed mm/min	Axial Force N	Tensile Strength (MPa)
1.	18	710	31.5	2000	90.56
2.	22	710	31.5	2000	79.85
3.	18	1400	31.5	2000	74.98
4.	22	1400	31.5	2000	91.54
5.	18	710	50	2000	75.89
6.	22	710	50	2000	74.89
7.	18	1400	50	2000	82.86
8.	22	1400	50	2000	91.56
9.	18	710	31.5	4000	80.54
10.	22	710	31.5	4000	67.56
11.	18	1400	31.5	4000	80.54
12.	22	1400	31.5	4000	67.56
13.	18	710	50	4000	90.56
14.	22	710	50	4000	92.85
15.	18	1400	50	4000	75.84
16.	22	1400	50	4000	81.45
17.	16	1000	40	3000	83.45
18.	24	1000	40	3000	79.86
19.	20	355	40	3000	70.52
20.	20	2000	40	3000	73.25
21.	20	1000	20	3000	92.53
22.	20	1000	63	3000	76.56
23.	20	1000	40	1000	89.56
24.	20	1000	40	5000	98.57
25.	20	1000	40	3000	110.25

3. ANN Modelling for tensile strength in FSW using MATLAB

3.1 Introduction

Artificial neural networks (ANNs) are biologically inspired by intelligent techniques. Artificial neural networks have been very popular in many engineering fields because of their fascinating features such as learning, generalization, faster computation and ease of implementation. ANNs are generally made up of a number of simple and highly interconnected processing elements organized in layers. Artificial neural networks have found extensive applications in diverse fields like manufacturing, signal processing, bio-electric signal classification, pattern recognition, speech recognition, image processing, communications, autonomous vehicle, navigation control of gantry crane to name a few. Even in manufacturing, ANN applications to cold forging for predicting the flow stress in hot deformation, for tool wear monitoring, for prediction of machining behavior, and for optimization of manufacturing processes among many others, are well documented and only a few illustrative references are cited here [10,11,12]. A multi layer perception was developed using MATLAB and used for the prediction of tensile strength. The BP was initially trained with experimental data and testing was performed with experimental data which was not used during training. Out of 25 data 70% data had taken for training and 15% data for cross validation and testing. All the Input and output data was normalized between 0.1 and 0.9 using the following equation [13]. Sample data has been shown in the table4.

$$Y_{(nor)} = (\frac{0.8}{\Delta})x + (0.9 - \frac{0.8x_{\max}}{\Delta}) \tag{1}$$

Y = Normalized value
x = value to be normalized
$\Delta = x_{\max} - x_{\min}$

Table 4 Experiments and results normalized data

Experiment reading No.	Tool Shoulder Dia. mm	Rotational Speed rpm	Welding Speed mm/min	Axial Force	Tensile Strength
1.	0.3	0.2	0.3	0.3	0.6
2.	0.7	0.2	0.3	0.3	0.4
3.	0.3	0.6	0.3	0.3	0.4
4.	0.7	0.6	0.3	0.3	0.6
5.	0.3	0.2	0.7	0.3	0.4
6.	0.7	0.2	0.7	0.3	0.4

3.2 Back Propagation Neural Network

For many years there was no rule available for updating the weight of a multi layer network undergoing supervised learning. The weight adaptation rule is known as back propagation. Neural networks are mathematical models composed by several neurons arranged in different layers, linked through the variable weights. These weights are calculated by an iterative method during the training process when the network is fed with a large amount of training data, input and output pairs that represent the pattern attempting to be modelled [10].

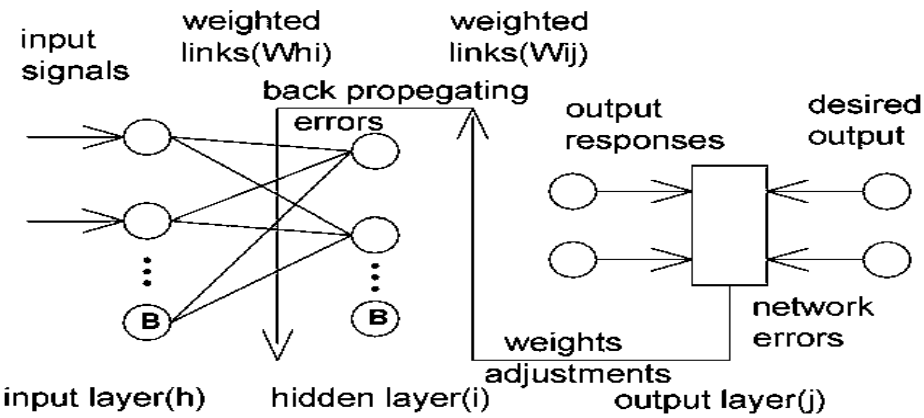

Fig.1. A back propagation network [10]

The back propagation algorithm defined two aspects of the network: first a forward sweep from the input layer to the output layer, and then a backward sweep from output layer to input layer. The forward sweep propagates input vector through the network to provide output at the output layer. The backward sweep is similar to the forward sweep, except that error values are propagated back through the network to determine how the weights are to be changed during the training. During the backward sweep, value passes along the weighted connection in the reverse direction to that which was taken during the forward sweep. Fig.1 shows a back propagation network a unit in the hidden layer will send the activation to the every unit in the output layer during the forward sweep and so during the backward sweep a unit in the hidden layer will receive an error signals from the every unit in the output layer [10]. In this present study, BP algorithm is used with a single hidden layer improved with training function called Traingdx is used. MATLAB platform is used to train and test the ANN. In the training, increased number of neurons (5–10) in a hidden layer had been used in order to define the output accurately. First layer of ANN is corresponding to input parameters like tool should diameter, tool rotation speed, welding speed and axial force. Outer layer of the ANN is for the tensile strength of welded component. After training the network successfully, it has been tested by using the known test data. The training parameters used in this investigation are listed in Table 5. The neural network described in this work, after successful training, was used to predict the tensile strength of friction stir welded joints within the trained range. Statistical methods are used to compare the results produced by the network. Errors occurring at the learning and testing stages are called the root-mean square (RMS), absolute fraction of variance (R^2), and mean error percentage values.

The final mean-square error is small as shown in Fig 2. Both the test set error and the validation set error has similar characteristics (green and red lines in the plot). No significant over fitting has occurred by iteration 124(where the best validation performance occurs).The linear regression between the network outputs and the corresponding targets is shown in fig.3 In our case, the output tracks the target very well for training, testing, and validation, and the r-value is a bit over 0.99 for the total response.

Table 5 ANN training data

1.	Network Configuration	4-8-1
2.	Number of hidden layer	1
3.	Number of hidden neuron	8
4.	Transfer function used	Logsig(sigmoid)
5.	Number of pattern used for training	70%
6.	Number of pattern used for testing	15%
7.	Number of pattern used for validation	15%
8.	Number of epochs	1000
9.	Learning factor	0.01
10.	Momentum factor	0.9
11.	Training function	Traingdx
12.	Max_fail	1000

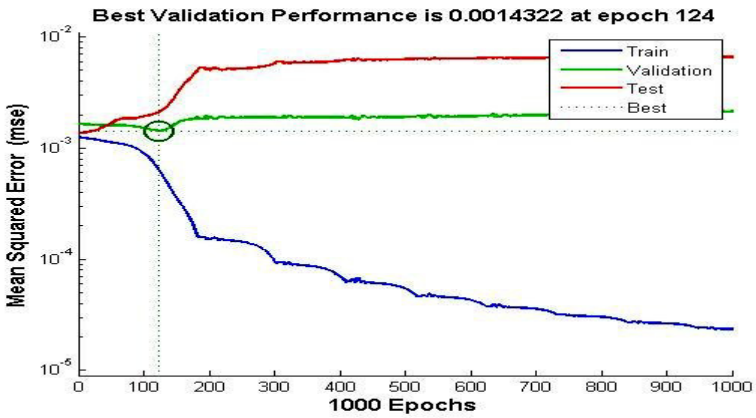

Fig .2 MSE error graph

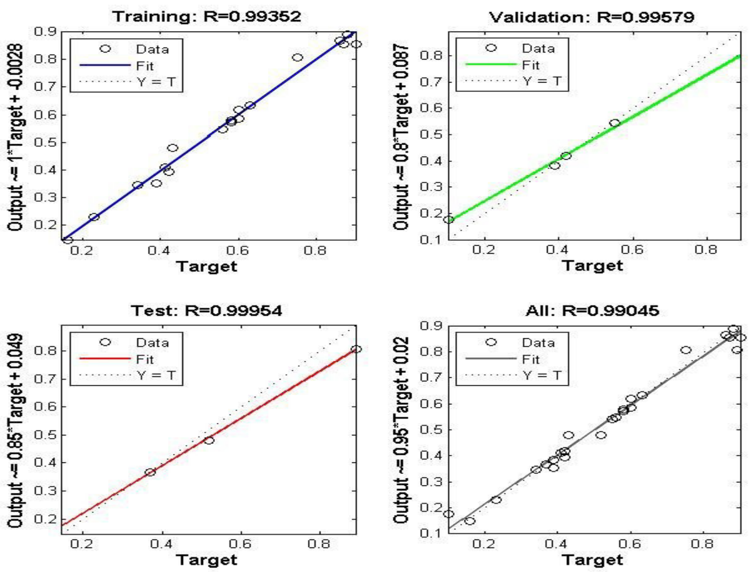

Fig.3 Performance analysis of trained network

Table 6 show variation of the experiment and ANN predicted result of mechanical properties of FSW Al plates. The measured and predicted output values are very close to each other. The error between experiment and predicted ANN architect 4-8-1 is less than 3 percent. So Train network can be used for the prediction of tensile strength for the given process parameters.

Table 6 Error between experiment and predicted tensile strength for various network

Input Parameter Model	Network Structure	Regression Value(R^2)	Sample Readings	Experimental Readings	Predicted Values	Error	Percentage Error (%)
1	4-5-1	0.945	1	0.60	0.602	-0.002	0.33
			2	0.37	0..367	0.003	0.81
			3	0..42	0..407	0.013	3.19
			4	0.60	0.617	-0.017	2.75
2	4-6-1	0.976	1	0.60	0.587	0.013	2.21
			2	0..37	0.388	-0.018	4.63
			3	0.42	0.399	0.021	5.26
			4	0.60	0.632	-0.003	5.06
3	4-7-1	0.964	1	0.60	0.603	-0.003	0.49
			2	0.37	0.378	-0.008	2.11
			3	0.42	0.409	0.011	2.68
			4	0.60	0.604	-0.004	0.66
4	4-8-1	0.980	1	0.60	.0602	-0.002	0.33
			2	0.37	0.365	0.005	1.36
			3	0.42	0.410	0.010	2.43
			4	0.60	0.617	-0.017	2.75
5	4-10-1	0.941	1	0.60	0.601	-0.001	0.16
			2	0.37	0.365	0.005	1.36
			3	0.42	0.470	-0.050	1.06
			4	0.60	0.615	-0.015	2.43

4. Conclusion

The developed neural network can be used to predict the tensile strength of welded aluminum plate for the given FSW process parameters. Results indicate that the networks prediction is very closed to the experiment results. Overall R value for training, validation and testing is bigger than 0.99. It is found that error in measured and predicted values are less than 3 percent for 4-8-1 ANN architect.

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