Prediction Of Tensile Strength Of Friction Stir Welded Joints Using Artificial Neural Networks

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Abstract

Friction Stir Welding (FSW) is a relatively novel welding technology, which has caught the interest of many industrial sectors due to its many advantages and clear industrial potential. This paper presents the prediction of tensile strength in a friction stir welded joints using Artificial Neural Networks (ANN). Experiments were conducted by varying the input parameters such as axial force, rotational speed and transverse speed, weld feed which play a key role in deciding the weld quality. A full factorial design was used for the experimental design. Three different types of neural network architectures namely Back Propagation Neural Network (BPNN), Radial Basis Function Network (RBFN) and Generalized Regression Neural Network (GRNN) have been used in predicting the tensile strength of the FSW process and a comparison is made between measured and predicted data.

Keywords- Artificial Neural Networks (ANN), Friction Stir Welding (FSW)

1. Introduction

Friction Stir Welding (FSW) is a revolutionary solid state welding which operates below the solidus temperature of the metals being joined and hence no melting takes place during the process. This process is a derivative of the conventional friction welding and is being used to produce continuous welded seams for plate fabrication. It requires a tool of harder material than the workpiece material being welded [1]. Friction Stir Welding is a hot-shear joining process in which a non-consumable, rotating tool plunges into a rigidly clamped workpiece and moves along the joint to be welded [2]. The cylindrical rotating tool used in FSW has a profiled threaded or unthreaded probe of length less than the weld depth, extruding from the tool shoulder. The FSW process is initiated by plunging of a rotating tool into the joint until the shoulder contacts the top surface of the workpiece. As the tool translates along the joint, heat is generated by rubbing action of tool shoulder against the workpiece. Additional heat is generated by visco-plastic dissipation of mechanical energy at high strain rates due to interactions between tool and workpiece [3]. The heat thus generated results in thermal softening of the material. The thermally softened material is contained at the underside by a backing plate, at the sides by non-softened parent material, and at the topside by pin force. The softened material is then forced to flow by the translation of the tool from the front to the back of the pin where it cools, consolidates and results in joint formation [4]. Previously, FSW was used for soft workpiece materials like aluminium alloys, lead, zinc, and magnesium. However, with the development of tools made from refractory material like tungsten and super abrasive materials like polycrystalline diamond (PCD) and polycrystalline cubic boron nitride (PCBN), FSW of high temperature materials was made possible [5].

Elangovan, Balasubramanian and Babu [6] developed a mathematical model using response surface method (RSM) to develop relationship between four process parameters and tensile strength for AA6061. The process parameters included tool rotational speed, welding speed, axial force and the tool pin profile. A similar study was carried out by Babu, Elangovan, V. Balasubramanian and M. Balasubramanian [7] but on a different aluminium alloy AA2219. Both the studies used Hooke and Jeeves search algorithm to achieve maximum tensile strength. Both the studies reported close match between the optimized values and the experimentally determined values. Lakshminarayanan and Balasubramanian [8] used one such statistical technique known as Taguchi technique to determine the effect of three process parameters, i.e. tool rotational speed, traverse speed, and axial force on the tensile strength of friction stir welded RDE-40 aluminium alloy. Jayaraman, Sivasubramanian, Balasubramanian and Lakshminarayanan [9] used a similar technique to find the effect of three process parameters on the tensile strength of friction stir welded A319 aluminium alloy. In both these studies, the authors performed Analysis of Variance (ANOVA) to identify statistically significant process parameters. Use of Artificial neural network (ANN) was proposed by Okuyucu Kurt and Arcaklioglu [10] to obtain correlation between FSW parameters and mechanical properties of aluminium plates. Their attempt was to correlate the parameters rather than to optimize them. The input parameters were weld speed and tool rotational speed while the output parameters included mechanical properties such as tensile strength, elongation, hardness of weld metal and hardness of heat affected zone. The obtained model was used to calculate mechanical properties of welded Al plates as a function of weld speed and rotational speed.

Recently, in the fields of materials joining, computer aided ANN modelling has gained increased importance. In the present work ANN model was developed to estimate Tensile Strength of a Friction stir welded aluminium plates subjected to the variation of the three input parameters of FSW process. A total of 27 experimental run with full factorial experimental design were investigated to predict the tensile strength using three neural network architectures namely Back BPNN, RBFN and GRNN.

2. Neural Networks

Artificial Neural Networks (ANNs) are information, processing systems, and can be used in several areas of engineering applications and eliminate the limitations of the classical approaches by extracting the desired information using the input data. For predicting the tensile strength a mathematical model is created using ANNs which represents the tensile strength in terms of input parameters. The advantage of the use of ANN for prediction is that they are able to learn from examples only and when learning is finished, they are able to catch hidden and strongly non-linear dependencies, even when there is a significant noise in the training set.

2.1 Feed Forward Neural Network (FFNN)

A standard feed forward neural network (FFNN) consisting of three layers viz. input, hidden and output layers and with an arbitrary activation function is a universal approximator. Fig.1 shows input neurons, hidden neurons and output neurons architecture of the model. The input layer consists of input parameters to the network such as axial force, rotational speed and transverse speed. The hidden layer consists of neurons, which learn to map points in the input space to coordinates in an output space. The output space is produced by processing the input through an activation function called transfer function. In this case a hyperbolic tangent function is chosen as the activation function since during testing it produces least mean square error among other functions such as logarithmic and Gaussian functions. The architecture of FFNN network model is shown in Fig. 1

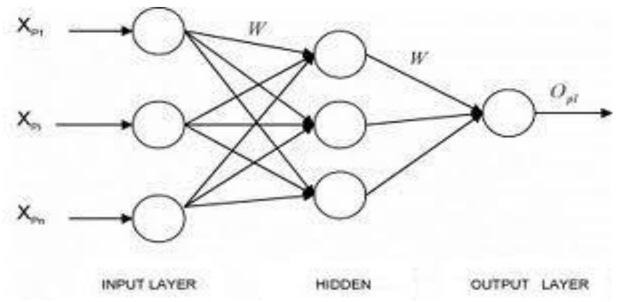

Figure 1 Architecture of FFNN network model

2.2 Radial Basis Function Network (RBFN)

Radial basis function networks are similar to feed forward networks which contain the input, hidden and output layers. However the differences lie in the fact that they contain only one hidden layer. They can be designed in a fraction of time it takes to train standard feed forward networks and work best when many training vectors are available. As shown in Fig. 2 the input layer in RBFNs contain one neuron for each type input and they feed information to each neuron in the hidden layer. The hidden layer has a variable number of neurons which consists of radial basis function. RBFN hidden layer units have a receptive field which has a centre that is particular input values at which they have a maximum output. The spread of the transfer function may be different for each input. The centres and spreads are determined for each input. The centres and spreads are determined by training process. The input values from the input layer are sent to the hidden neurons which compute the Euclidean distance of the test case from the neuron's center point and then applies the radial basis function to this distance using the spread values. The value coming out of a neuron in the hidden layer is multiplied by a weight associated with neuron and passed to the summation which adds up the weighted values and presents this sum as the output of the network. Also a bias value can be multiplied to the weights and presented to the summation layer in computing.

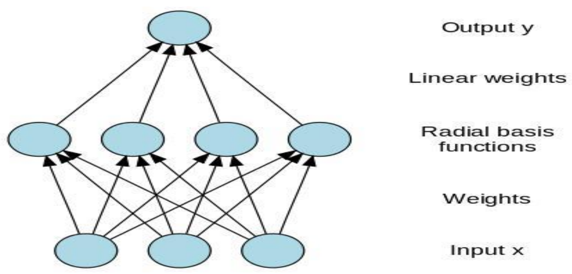

Figure 2 Architecture of RBFN network model

2.3 Generalized Regression Network (GRNN)

Generalized Regression neural network comes under the category of probabilistic neural networks. A GRNN is a one pass learning algorithm and like other neural networks the GRNN requires only a fraction of training samples as a back propagation network needs. The GRNN processes an input layer, pattern layer, summation layer and output layer as shown in the Fig.3.The probability density function used in GRNN is the Normal Distribution. In training of network, radial basis and linear activation functions are used in hidden and output layers. The advantages of GRNN are that it processes relatively simple and static with two layers, namely pattern and summation layers. Once the input goes through each unit in the pattern layer, the relationship between the input and the response would be "memorized" and stored in the unit. The network is able to learning from the training data by "1-pass" training in a fraction of the time it takes to train standard feed forward networks.

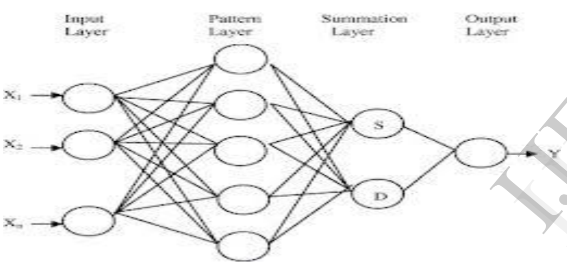

Figure 3 Architecture of GRNN network model

3. Experimental Work

Based on the previous literature [6-10] among many controllable process parameters affecting the tensile strength, the primary process parameters such as axial force, rotational speed and transverse speed were selected as process parameters for this investigation. The above parameters are contributing to the heat input and subsequently influencing the tensile strength variations in the friction stir welded aluminium alloy joints. Initially trail experiments were carried out on aluminium plates to determine the feasible levels of FSW process parameters. The process parameters and their levels used in the experiments are given in Table 1. The experimental plan used for experimentation is shown in Table 2. The base metal used in this work was aluminium with dimensions of 200mm x 100mm x 5mm. The welding was performed on vertical milling machine (HMT made) as shown in Fig. 4. The tool used for FSW process was of cylindrical pin type. The welded joints were prepared according to standards using a power hacksaw. Three tensile specimens were prepared from each joint to evaluate the tensile strength. Tensile test was carried out on Universal Testing Machine (UTM).

TABLE 1 PROCESS PARAMETERS AND THEIR LEVELS

Process parameters	Levels		
	1	*2*	*3*
Axial force (kN)	3	5	7
Rotational speed (rpm)	900	1100	1300
Transverse speed (mm/min)	30	50	70

TABLE 2 EXPERIMENTAL PLAN

Expt. No.	Axial force (kN)	Rotational speed (rpm)	Transverse speed (mm/min)
1	3	900	30
2	5	900	30
3	7	900	30
4	3	900	50
5	5	900	50
6	7	900	50
7	3	900	70
8	5	900	70
9	7	1100	70
10	3	1100	30
11	5	1100	30
12	7	1100	30
13	3	1100	50
14	5	1100	50
15	7	1100	50
16	3	1100	70
17	5	1100	70
18	7	1100	70
19	3	1300	30
20	5	1300	30
21	7	1300	30
22	3	1300	50
23	5	1300	50
24	7	1300	50
25	3	1300	70
26	5	1300	70
27	7	1300	70

Figure 4 Joining of aluminium plates using FSW process

4. Results and Discussions

The neural network toolbox in MATLAB 2010 was utilized to develop the ANN model for the present problem. The input layer consists of three parameters viz. axial force, rotational speed, transverse speed and the output layer corresponds to tensile strength. The data were first fed into the network and then simulated to obtain the output. While creating the network the following parameters were varied to obtain different results viz. maximum number of neurons and spread constant. This was achieved by trial and error method. Fig. 5 shows the variation of experimental and predicted values using BPNN, Fig 6 depicts the experimental and predicted values using RBFN and Fig 7 depicts the experimental and predicted values using GRNN. From Fig. 5, Fig. 6 and Fig. 7 it is seen that the results predicted using BPNN, RBFN and GRNN are in close agreement with experimental values. Fig. 8 depicts the variation of mean of tensile strength with respect of input process parameters such as axial force, rotational speed and transverse speed. From the plot it is observed that the tensile strength is increasing as the axial force increases, it is increasing upto a certain level and then decreases with increase of both rotational and transverse speed values. Fig. 9 interprets Interaction plots of tensile strength values with respects to various input parameters. Unlike standard feed forward networks, GRNN estimation is always able to converge to a global solution and won't be trapped by a local minimum.

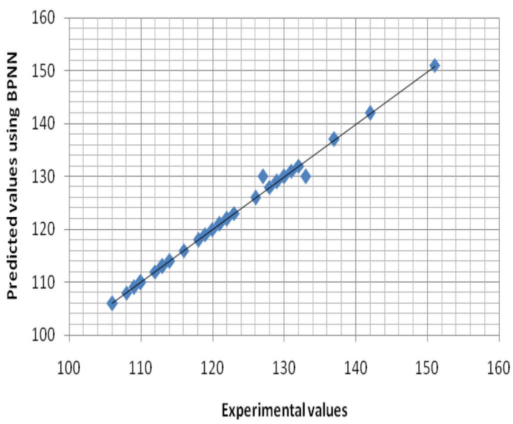

Figure 5 Experimental values vs. predicted values (using BPNN)

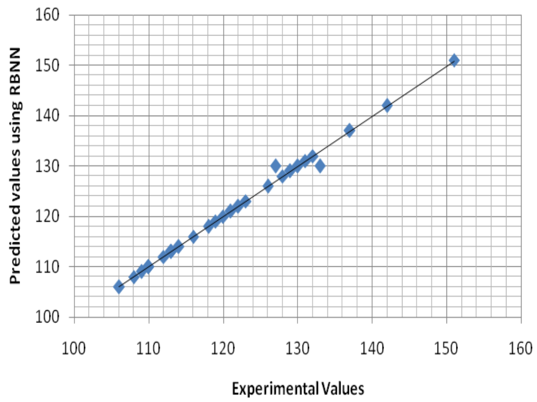

Figure 6 Experimental values vs. predicted values (using RBNN)

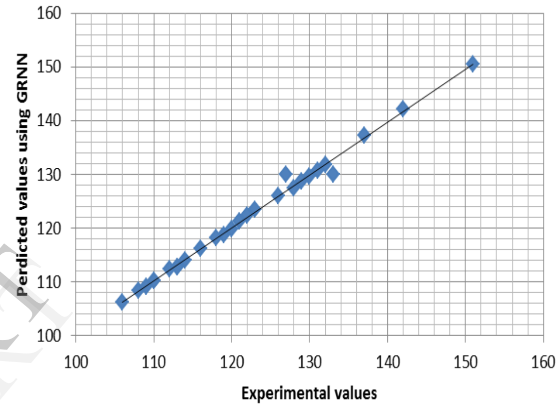

Figure 7 Experimental values vs. predicted values (using GRNN)

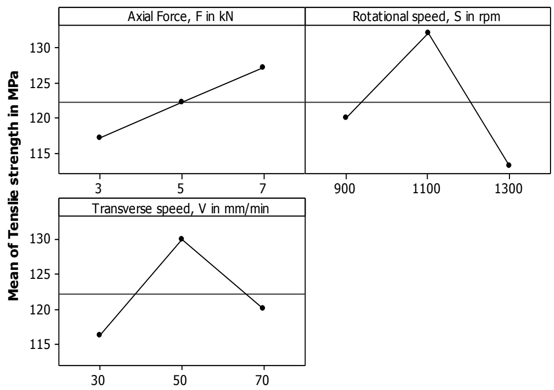

Figure 8 Main effect plots for mean of tensile strength

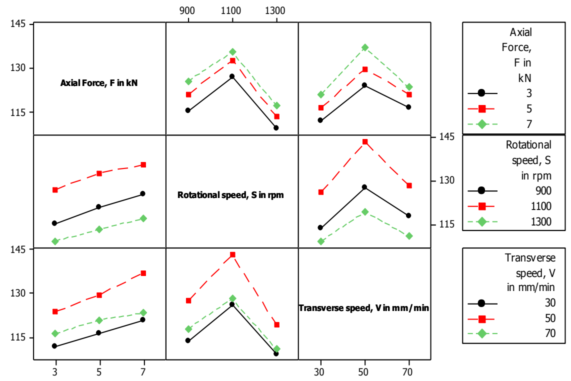

Figure 9 Interaction plots of variation of tensile strength

5. Conclusions

Experiments were conducted on FSW welding machine using full factorial design and tensile strength of specimens was determined using universal testing machine. Based on the experimental results it was observed that the tensile strength of welded joint is increasing linearly with increase in axial force and as the rotational speed and transverse speed increases it is increasing up to a certain level and then onwards it is decreasing. The tensile strength in a friction stir welded butt joint was predicted using three different types of neural network architectures namely Back Propagation Neural Network (BPNN), Radial Basis Function Network (RBFN) and Generalized regression network (GRNN) performed using ANN. The results indicated that the predicted values are in good agreement with the experimental values. Hence the ANN technique is straight forward method used for prediction of tensile strength in FSW process and it can be applied to many engineering applications.

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7. References

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