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Research Paper

ARTIFICIAL NEURAL NETWORKS IN TENSILE STRENGTH AND INPUT PARAMETER PREDICTION IN FRICTION STIR WELDING

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Welding speed and rotational speed have been singled out as the most influential welding parameters which affect the tensile strength as well as the hardness in Friction Stir Welding (FSW). It is however problematic to determine the possible welding speed and rotational speed given the Ultimate Tensile Strength (UTS) since there are several combinations of welding speeds and rotational speeds that can yield the same UTS. At the same time, however, the input parameters predicted may not be available on the machine. This research is therefore aimed at using Artificial Neural Networks (ANN) in predicting the UTS given rotational speed and welding speed as well as exploring the possibility of obtaining the input parameters given the output UTS.

Keywords: Friction stir Welding, Input parameter prediction, Tensile strength prediction, Artificial neural network

INTRODUCTION

Aluminium alloy 6061 is recognised as a medium to high strength heat-treatable alloy with good corrosion resistance. However it has reduced strength in the weld zone. This material has found applications in heavy duty structures. These include; rail coaches, ship building, aerospace, truck frames, etc. (Aalco, 2013). Material AA7075 has found similar applications in aerospace as well (Elatharasan and Senthil, 2012).

Materials AA6061 and AA7075 have been previously successfully joined by FSW and an attempt to optimise the welding parameters was made by Elatharasan and Senthil (2012) using Response Surface Methodology (RSM). In a similar attempt, Palanivel and Mathews (2012) used RSM in optimising FSW of AA5083-H111. The same method was again applied on AA6061-T4 by Heidarzadeh *et al.* (2012).

Lakshminarayanan and Balasubramaian (2009) outlined that the selection and control

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of welding parameters is very important in attaining the maximum strength. It was reported that ANNs can give better results compared to regression analysis when dealing with data following a non-linear behaviour. A small number of experiments can be used to develop a model although a bigger number of experiments will provide more accurate results.

ANNs are biologically motivated computational models composed of neurons that can solve complex problems in real life situations, Lakshminarayanan and Balasubramaian (2009). Feed forward back propagation is one of the most commonly used network architectures available in neural networks. The Levenberg-Marquardt training algorithm is one of those algorithms used to train the neural network. ANNs have been applied in the prediction of FSW characteristics by Yousif *et al.* (2008) using an aluminium alloy. In a different experiment Okuyucu *et al.* (2007) applied ANN in calculating mechanical properties of an aluminium sample joined by FSW. In all cases where ANNs were applied, it was found that they produce good results especially when sufficient input data is used. Besides the application of ANNs in FSW, they have also been used successfully in other welding processes (Nagesh and Datta, 2002 and 2010). They used ANNs to predict weld bead geometry and penetration in shielded metal-arc welding process. They discovered that there was only a small error in the use of ANNs. Elsewhere, Sanjay *et al.* (2005) used ANNs in the prediction of drill wear in which input parameters were given as spindle speed and feed, drill size, torque, machining time and force. Flank wear was the estimated output from the ANN. ANNs are also used in robotics, image processing as well as in other intelligent systems.

It is against this background that although some researches have been done, ANNs have only been applied in prediction of mechanical properties or other direct outputs of a process. The prediction of input parameters given the output has not been attempted especially in FSW using ANN.

EXPERIMENTAL PROCEDURE

Preliminary trials revealed that welding speed as well as rotational speed are the main parameters which influence the mechanical properties of the joints made by FSW. Cross-sections measuring 120 x 75 x 6 mm were used in the FSW of AA6061 and AA7075. The welds were singe pass but joints which were performed on a conventional milling machine. A tool made of high-carbon high-chromium steel was used for the FSW process. The shoulder diameter was 16 mm, and it had a tapered cylindrical profile with a right hand thread of 1mm pitch on a 5.8 mm pin. The root diameter was 6 mm while the tip diameter was 5.5 mm. All experiments were done using anticlockwise spindle rotation. The tensile specimens were cut transverse to the joint using a wire EDM machine. These specimens were cut according to the American Society for testing and materials standard. The tensile strength of the two base materials AA6061 and AA7075 are 310 and 572 Mpa respectively. The chemical composition of the two alloys is given in Table 1.

Process Variables

The rotational speeds were varied between 800 and 1200 rpm in steps of 200 rpm while

Table 1: The Percentage Chemical Composition of Various Elements in AA6061 and AA7075

	Mn	Fe	Mg	Si	Cu	Zn	Ti	Cr
AA6061	0 – 0.15	0 – 0.7	0.8 – 1.2	0.4 – 0.8	0.15 – 0.4	0 – 0.25	0 – 0.15	0.04 – 0.35
AA7075	0 – 0.30	0 – 0.5	2.1 – 2.9	0.0 – 0.4	1.2 – 2.0	0 – 5.60	0 – 0.20	0.18 – 0.28

Table 2: Process Variables Used in the FWS Experiments

Rotational Speeds (Rs.)	800, 1000 and 1200 rpm
Traverse Speed (Ts)	20, 30, 60 and 90 mm/min

the welding speeds (traverse speeds) were selected among 20, 30, 60 and 90 mm/min. These were selected in consideration of the speeds available on the milling machine spindle rotation as well as feed rates available.

A total of (3 x 4) 12 experiments were carried out. The various rotational speed and traverse speed variations and the tensile strength obtained on the universal tensile testing machine are as shown in Table 4.

METHODOLOGY OF ANN EXPERIMENTAL DATA MODELLING FOR OPTIMISATION AND PREDICTION

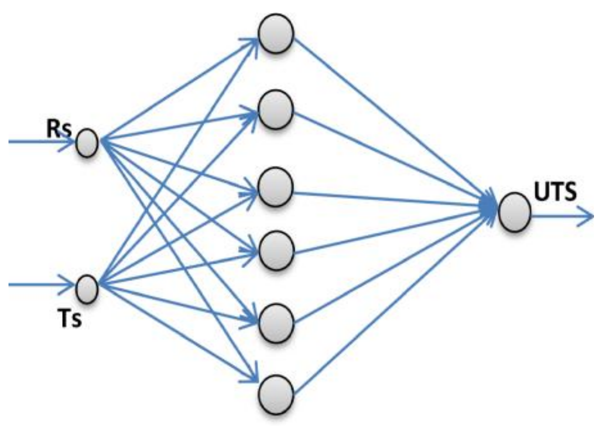
Due to the complex nature of FSW, we encounter non-linear relationships between the input parameters, i.e., welding speed and rotational speed when compared to the outputs which include tensile strength, yield strength and hardness. When we encounter such a situation, artificial neural networks can then be applied since they have the ability to learn from examples, i.e., training.

ANNs have been described as the model of the brains cognitive process (Rajagopalan, 2006). This is because in their operation, they try to mimic the way the human brain operates in solving complex problems.

ANN for Tensile Strength Prediction

A three layer ANN was designed and implemented in MatLab Version 7.5. The neural network had one input layer, one hidden layer and a single output layer. There were two inputs into the system namely; the welding speed and the rotational speed. There was a single output which was the tensile strength. A Levenberg-Marquardt training algorithm was used to train the ANN.

Figure 1: The ANN Architecture Used in UTS Prediction



The network was chosen arbitrarily since there is no clear procedure in choosing a network to use in ANN. A total of 6 neurons were used in the hidden layer and there was one output neuron in the output layer. Logsig and pure linear activation functions were used in the network. Out of the 12 data sets obtained through the experiments, nine were used as training data set and 3 were used for testing and the results are as shown in Table 4.

RESULTS AND DISCUSSION

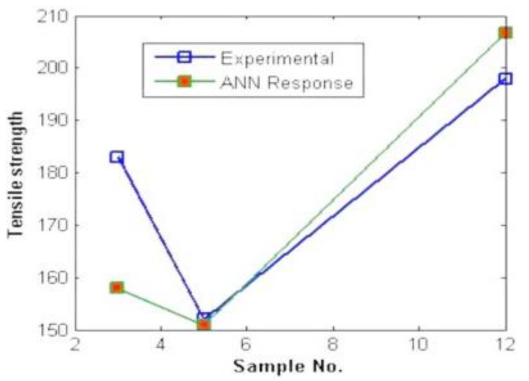
Tensile Strength Prediction

Although a limited amount of training data was used, the ANN has shown that it can give results close or almost same as the experimental results. Perfect results can be expected if the predictions are made within the training data set. This is proven by the output of sample number 3. It is relatively easy to develop and train a neural network that can predict the tensile strength given the input parameters. The error in the prediction of the tensile stress was calculated based on mean Absolute Percent Error (APE) Malinov *et al.* (2001) and it was found to be 6.2%. This was caused by the relatively less training data used. The ANN response from the test data is given in Table 3.

Table 3: ANN Response from the Testing Data

R_s	T_s	UTS	NN Response
800	60	183	157.9
1000	20	152	150.8
1200	90	198	206.6

Figure 2: Actual vs Predicted Values of Tensile Strength



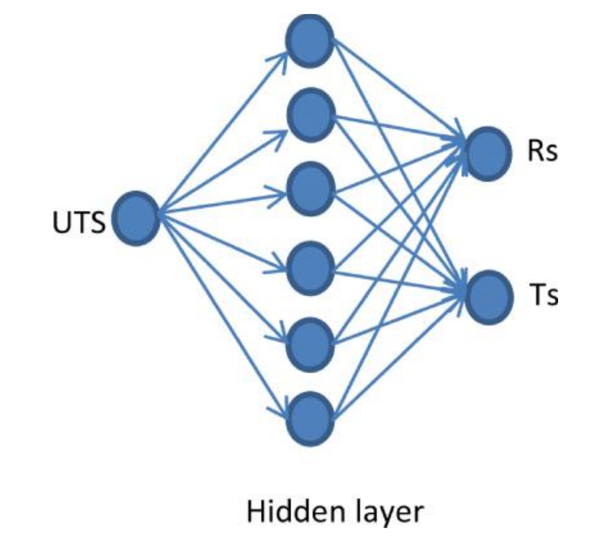
Input Parameter Prediction

An ANN with one input, one hidden layer with 6 perceptrons and two outputs was used in input parameter prediction. The UTS values obtained from experimentation together with the input parameters used were used to train the neural network in what could be termed 'reverse prediction' (Johnson and Campeau, 2005). It has been proven by the neural network that it is possible to predict the input parameters given the output parameters (Table 4). However, this type of prediction using ANNs is very complex. This is because there are several combinations of input parameters that can give a single output in FSW. For example using 800 rpm with 20mm/min gives an almost similar result of 192/193 MPa which can also be obtained using 1200 rpm and 60 mm/min. According to the ANN, a UTS of 192 MPa can be obtained using 1044.09 rpm and a traverse speed of 50.3 mm/min. Although this is possible, it may become a problem if these parameters cannot be obtained on the machine.

Table 4: ANN Response to Input Parameter Prediction

R_s	T_s	ANN Rs	ANN Ts	UTS
800	20	1044.09	50.3	192
	30	1030.02	50.2	187
	60	1018.76	50.12	183
	90	897.76	49.3	140
1000	20	931.52	49.53	152
	30	945.56	49.63	157
	60	982.18	49.88	170
	90	1015.95	50.11	182
1200	20	996.25	49.97	175
	30	1030.02	50.20	187
	60	1046.9	50.32	193
	90	1060.97	50.42	198

Figure 3: ANN for Input Parameter Prediction



Based on the observations made, there is a possibility of getting better results if the training data is segmented or grouped into groups according to the available spindle speeds. In our case, we can make three groups based on the rotational speeds 800, 1000 and 1200 rpm. The networks are trained independently for each group and then used to determine the input parameters required when given an output. Obviously all the three groups will give a valid result but the selection will be done based on availability of the input parameters on the machine.

CONCLUSION

It is possible to get good results when ANNs are used to predict the tensile strength using welding speed and rotational speed as the input parameters especially when sufficient data is used to train the ANN. Input parameter prediction is, however, not an easy task due to the several number of possible combinations of input parameters that can give that same output. Also the input values depend on the availability of the spindle speeds and feed rates provided on the machine. Further work still needs to be done in grouping the input parameters, train the network independently and then observe the outputs. Furthermore, a more desirable though complex method can be devised which allows the determination of all the possible input parameters at once without the need to group the input parameters. This is because grouping input parameters will obviously require more input data to train the ANN.

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