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CONTENTS

Parametric optimization of friction stir welding for electrical conductivity of aluminium joints using ANN approach

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ABSTRACT: Friction Stir Welding is a newer replacement of conventional fusion welding for joining low melting point materials. The solid-state nature of this unique process makes it almost defect –free welding process for critical joints. The FSW set up for the experimentation was completed by developing necessary tool and fixture and joints were made on Universal Milling machine. The present research work investigates the effect of some desired input parameters for Friction Stir Welding on the electrical conductivity of AA1350 aluminium butt joints. Rotational speed of tool, Tool Traverse speed (welding speed), and tool tilt angle were opted as input parameters. Objective of the whole experimentation is to find the best combination of input parameters for maximum conductivity at nugget area of FSW joint. After experimentation with selected parameters, investigation by ANN is done. Back propagation (BP) algorithm is utilised for developing the network. After ANN modelling, optimization of FSW parameters by full factorial method is also investigated. The ANN result outcome and the experiment data was found to be in good agreement. The optimum value of electrical conductivity of welded joints obtained was 52.7 IACS.

Key words: Artificial Neural Network, Friction Stir Welding, Solid State Welding, full factorial method

The Welding Institute (TWI), Cambridge (UK) was the first ever organization to introduce Friction Stir Welding as a commercial solid state joining method in 1991 (Thomas, 1991). Later this process became popular for its application in Aluminium alloys [Gibson *et al.,* 2014). FSW is recognised as the key development in the defect-free metal joining of low melting point alloys (Özel and Karpat, 2005). This metal joining technique is simple and green process (Chryssolouris *et al*., 1996). This process was later adopted commercially in aerospace aluminium alloys welding as well as other metallic alloys that faced problems to be welded with traditional welding (Mishra and Ma, 2005). FSW is basically a mechanical way of joining low-melting point alloys in which a rotating tool having shoulder, mostly with threaded pin, is made to insert into the gap of joining plates (Nandan and Tewari, 2021). The tool is given a dwell time for a few seconds before the material softens into a paste, after which it is run at constant speed to make the FSW joint (Munoz-Escalona and Maropoulos, 2010). Thus, an FSW tool heats the joining pieces as well as retains the plastic state material below its shoulder (Kapoor and Nandan, 2021). The weld resulted by FSW is of fine grain which provides good mechanical properties (Lakshminarayanan and Balasubramanian, 2008). FSW can be understood as a mechanical way of joining using process of extrusion by a rotating tool (Threadgill *et al.,* 2009).

Optimization techniques is the statistical tool to solve the engineering problems (Sharma and Kumar, 2020). A broad variety of non-linear modelling implementations and optimization issues were used for ANNs (Artificial Neural Networks) in the past (Kechagias and Iakovakis, 2009). All these studies find that ANN can be utilized effectively for modelling of complex relationship among many inputs as well as outputs to predict precisely the behaviour of outputs (response variables) once the input parameter values are varying within the study range (Benardos and Vosniakos, 2002). The current research work explores the relationship between electrical conductivity and electrical conductivity as input parameter of thick AA1350 grade aluminium plates butt welded with the help of FSW.

MATERIALS AND METHODS

Experimental set up was installed using a traditional Universal Milling machine of HMT make with a 7.5 HP motor (Fig. 1). Development of FSW tool was done by machining HSS material of shoulder diameter 25mm and straight threaded pin diameter 12mm. Strong fixtures along with backing plates were made in the shop floor for defect-free welding. The straight threaded pin was necessitated because of larger heat input for thick plate joining. AA1350 Aluminium alloy of length 100mm, breadth 100mm and thickness 12.7mm cut from rolled plate and two such samples joined together by FSW to make a welded sample size of 200x200x12.7. Samples were cut as per specification. As no previous literature data was available for FSW of thick Al plates, exhaustive and careful trail runs were required on the milling machine. First of all, the machine's rpm range for satisfactory welding were achieved through a number of trials. At the same time, a suitable travel speed for welding was also determined. Three parameters Tool Travel Speed, Tool rpm and Tool tilt angle were selected as input parameters for their effect on electrical conductivity as an output response parameter. Experimentation was done by adopting full factorial orthogonal array. An experimentation of 27 runs was conducted on different settings as per full factorial table. Three levels of each parameter were decided (Table1). With the help of experimental results, ANN was applied to model the input and output parameters. Design of Experiments (DOE) is used to find the best input parameters setting of the process to optimize performance characteristics (Tewari *et al.,* 2021).

Electrical Conductivity tests (Fig. 2) were performed under laboratory conditions at BHEL- Rudrapur plant. During the test, the room temperature was maintained continuously at 20p C as per standard. The below equation was used for compensation of any temperature difference error:

S1= S2/ [1+a X (T1- T2)], Where S2= Conductivity at observed temperature

S1= Conductivity at 20p C

a=Temp. Coefficient of Al alloy=0.0043

T1= 20p C

T2= readings Temperature (taken as 23p C)

Table 1: Input Parameter with Levels

S. No	Process Parameter	Units	Level 1	Level 2	Level 3
1.	Welding Speed	mm/min	80	100	125
2.	Tool rpm	rpm	560	710	900
3.	Tool Tilt Angle	degree	0	1	2

Fig. 1: Universal Milling Machine

Fig. 2: Electrical Conductivity Machine (Courtesy: BHEL-Rudrapur)

Modelling Framework

This research study has aimed to establish an ANN Network to estimate the electrical conductivity (output) of thick AA1350 aluminium plates during FSW according to Kechagias *et al.* (Kechagias *et al.,* 2010). The three input parameters (Welding speed, Tool tilt angle, and Rotational Speed) with 3 levels each of the ANN were selected (Table 1). The experimental data of Table 2, used in modelling procedure, was linked to selected input parameters as well as the output parameter. The experimental results obtained by 27 runs were classified into 3 categories, i.e., training, validation and the test samples during the frame of the ANN modelling process. These are shown to the network throughout training, and the network is modified by its errors. For testing the generalization of the network, validation samples are used till generalization stops improving. Test samples do not influence training and thus have an independent network output assessment both during and after training called confirmation runs. Seventeen (17) samples (60%) have been utilized for training, five samples (20 per cent) for testing purposes, and five (5) samples (20 per cent) for validation.

There are several architectural styles available for ANN. For the prediction of electrical conductivity, this work was performed using the FFBP (feed-forward with back propagation) learning. These network types have an X-input layer, hidden layers of one or more multiple neurons along with a Y-output layer. The hyperbolic tangent sigmoid hidden layer function is used in the chosen ANN

Table 2: Full factorial experimental data and results

S. No	Welding Speed (mm/min)	Rotational Speed (rpm)	Tool Tilt Angle (degree)	Electrical Conductivity
1.	80	560	0	50.7
2.	80	560	1	48.6
3.	80	560	2	46.1
4.	80	710	0	48.8
5.	80	710	1	47.5
6.	80	710	2	46.6
7.	80	900	0	47.4
8.	80	900	1	46.9
9.	80	900	2	46.7
10.	100	560	0	52.6
11.	100	560	1	49.5
12.	100	560	2	47.9
13.	100	710	0	50
14.	100	710	1	48.8
15.	100	710	2	47.9
16.	100	900	0	48.2
17.	100	900	1	48.3
18.	100	900	2	48.4
19.	125	560	0	54.1
20.	125	560	1	51.4
21.	125	560	2	50.2

whereas the function of linear transfer has been used for the output layer. Table 1 includes the three procedure parameters of the input vector. The output layer contains the efficiency measure. For the initial training process, several experiments and failures have been carried out in order to measure the best number of hidden layers and neurons. A minimum error between the ANN estimates the output with one hidden layer of 10 neurons (Fig.3) of experimental data was observed. Back propagation ANNs are prone to overtraining issues which may restrict the ANN's generalization ability. Overtraining typically takes place in ANNs with plenty of flexibility and after a number of training cycles, in that, the output of the training data set is increased whereas validation data set performance is decreased. Therefore, the network size, in the present case, is small in respect of the data set training and as shown in Fig. 4, the validation performance is sufficient if ANN training ends.

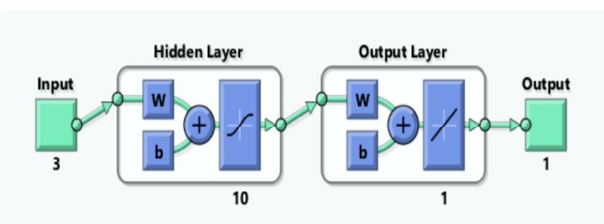

Fig.3: The ANN Architecture

The mean square error (MSE) of predicted results is used to calculate network efficiency with regard to the value of the experimental data. MSE is hereby defined as the average square difference between network outputs and experimental values. Lower the MSE values, the better it is. Null indicates no error. Regression (R) is another indicator of the performance of network efficiency. Relation between response values and the experimental values is indicated by Regression value. An R-value of one implies a close relationship (Fig. 4), 0 implies a random relationship. Following formula shows the mathematical relationship between the input and output parameters (Ghetiya and Patel, 2014).

$$y = purelin\ (\Sigma_{i=1}^{s}\ w2_i\ {*}tansig(\Sigma_{j=1}^{n}(w1_{ij}\ {*}x_j + b1_i) + b2) \quad (1)$$

Where:

y: Output response

S: No of hidden neurons

N: No of input variables

w1: Vector of weights between the input and the hidden layer.

w2: weight vector from the hidden layer to the output.

b1: Vector of biases of the neurons in the hidden layer.

b2: Bias of the output neuron.

Purelin: Linear transfer function and purelin (z) = z

tansig: Hyperbolic tangent sigmoid function and

$$tansig\ (z) = \frac{2}{1+6^{-zz}} - 1 \quad (2)$$

The experimental data is hereby used exclusively for calculation of weights and biases of Eq. 1during the learning phase of the ANN. (Table2).

RESULTS AND DISCUSSION

The electrical conductivity is predicted by using the trained ANN model within the defined range. Statistical tools and techniques are utilized for comparison of results produced by the network. The root-mean-square (RMS), mean error percentage and absolute fraction of variance (R^2) values are used to describe errors that occur during the learning and testing periods. This was carried out by checking the behaviour of the response variable with variations in the travel speed values, Rotational Speed, and Tool tilt angle. Fig. 4 depicts the nature of regression to be linear as regards network outputs versus goals. In present case, the objective for training, testing, and validation was matched with the performance of the model, with R-values of 0.92, 0.96, and 0.88, respectively. The R-value is approximately 0.93 for the total response. The final MSE is also shown in Fig. 5. The MSE estimated prediction error is extremely low (i.e., 0.25231). The set error for both testing and validation has similar characteristics. Best validation performance was found to be at iteration 11. No significant over fitting was observed at this point. Fig. 4 explains this validation performance. Therefore, once the Welding speed, rotational speed, and tool tilt angle have been provided values within the valid range, the ANN will accurately estimate output response.

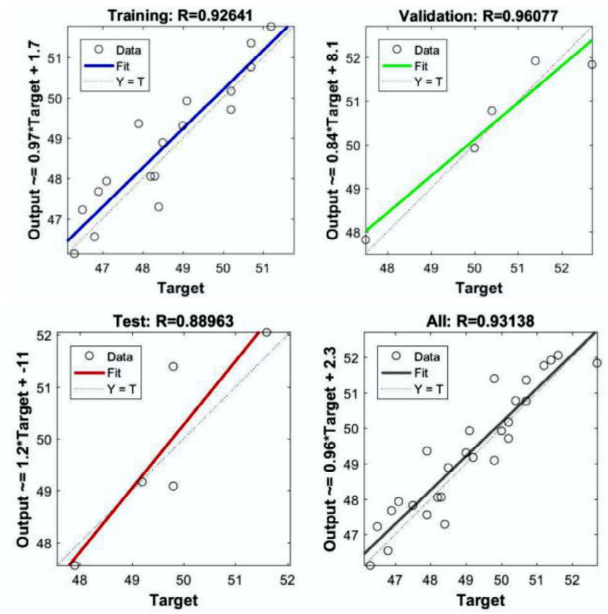

Fig.4: Correlation curves for Different ANN Stages

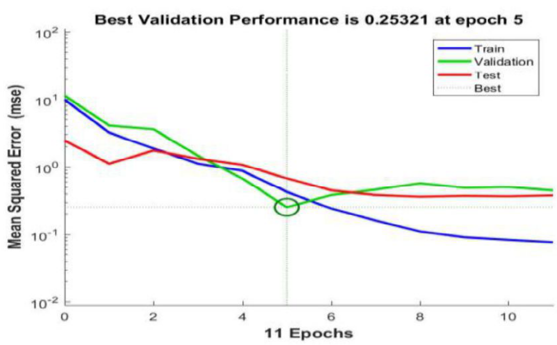

Fig. 5: Performance Curves for Various ANN Stages

The electrical conductivity of the welding joints is analysed to study the effect of the FSW process parameters using full factorial method. The main effect plots are drawn in Fig.6. Evidently, the travel speed increases the cause of rise in electrical conductivity of weld nugget zone, and high rotational speed as well as tool tilt angle are the reasons for decrease in electrical conductivity. The best combination of input variables for maximum electrical conductivity are 125mm/min, 560 rpm, 0æ% and 52.7 IACS. The comparative effect of input parameters on output parameter were Tool rotation > Travel speed > Tool tilt angle.

Table 3 shows the optimum results and the confirmation test values. This proves that estimation is quite correct and prediction of percentage error is precise. The error, as a result of confirmation test, is 2.58 % by the proposed method under acceptable range.

Table 3: Optimum Results and Confirmation Test

Optimum parameter			Response parameter	Actual Value	% Error
TS	RS	TA			
125	560	0	52.7	54.1	2.58

CONCLUSION

The experimental data utilized for the ANN modelling process has been obtained through a set of properly chosen experiments, design of experiments as per the full factorial method. Precise prediction for Electrical Conductivity under the given conditions can be made with the developed neural network. Experiment results are in close agreement with networks prediction. The present technique was able to generate best combination of input parameters for the optimum level of Electrical Conductivity at the stir zone of FSW joint. Results show that high welding speed, low rotational speed, and low tilt angle are favourable for better

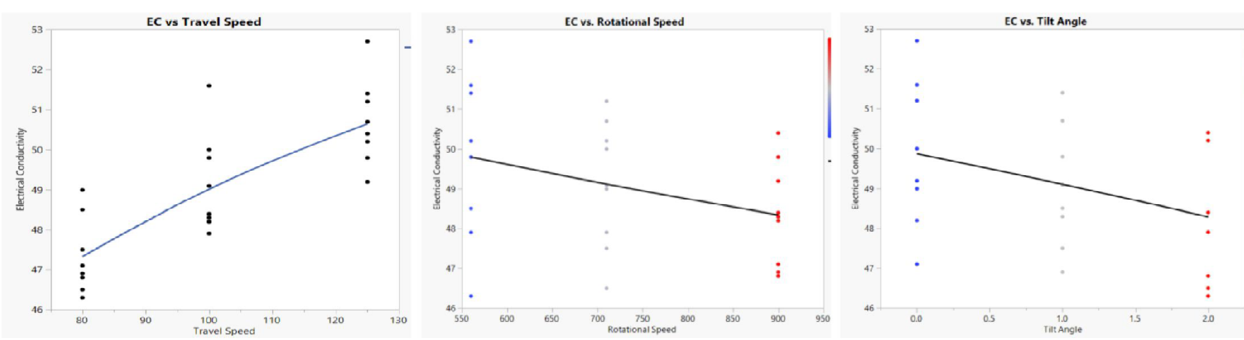

Fig.6: Main effect plot for means

conductivity at the joints. To be on the safer side, Friction Stir welded joint, the heat input and the material mixing in the stir zone have to be properly combined. Thus, Parameters that provide either lower input heat or higher input heat contribute negatively for sound FSW welds. Hence too high a traverse speed combined with low tool rpm needs to be avoided for conditions leading to weaker joint. Similarly, too low a travel speed combined with high tool rpm are detrimental for better joint.

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