Comparison of response surface model with neural network in predicting the tensile strength of friction stir welded RDE-40 aluminium alloy

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Abstract

Friction stir welding (FSW) is an innovative solid state joining technique and has been employed in aerospace, rail, automotive and marine industries for joining aluminium, magnesium, zinc and copper alloys. The FSW process parameters such as tool rotational speed, welding speed, axial force etc., play a major role in deciding the weld quality. This paper focuses two innovative methods such as response surface methodology and artificial neural network are used to predict the tensile strength of friction stir welded RDE-40 aluminium alloy. The experiments were conducted based on three factors, three-level, and central composite face centered design with full replications technique and mathematical model is developed. The results obtained through response surface methodology were compared with artificial neural networks. It was found that the error rate predicted by the artificial network was smaller than predicted by the response surface methodology.

Key words: Friction stir welding, aluminium alloy, tensile strength, response surface methodology, artificial neural network

I. INTRODUCTION

Generally, the quality of a weld joint is directly influenced by the welding input parameters during the welding process; therefore, welding can be considered as a multi input multi-output process [1]. Unfortunately, a common problem that has faced the manufacturer is the control of the process input parameters to obtain a good welded joint with the required weld quality with minimal detrimental residual stresses and distortion [2]. Traditionally, it has been necessary to determine the weld input parameters for every new welded product to obtain a welded joint with the required specifications. To do so, requires a time-consuming trial and error development effort, with weld input parameters chosen by the skill of the engineer or machine operator [3]. Then welds are examined to determine whether they meet the specification or not. Finally the weld parameters can be chosen to produce a welded joint that closely meets the joint requirements. Also, what is not achieved or often considered is an optimized welding parameters combination, since welds can often be produced with very different parameters. In other words, there is often a more ideal welding parameters combination, which can be used if it can only be determined. In order to overcome this problem, various prediction methods can be applied to define the desired output variables through developing mathematical models to specify the relationship between the input parameters and output variables. In the last two decades, design of experiment (DOE) techniques has been used to carry out such prediction. Evolutionary algorithms and computational network have also grown rapidly and been adapted for many applications in different areas [4]. Recently, in the fields of materials joining, computer aided ANN modeling has gained increased importance [5]. Most researchers have investigated the prediction of process parameters for better weld bead quality of fusion welding processes. Hasan Okuyucu [6] et al., (2005) showed the possibility of the use of neural networks for the calculation of the mechanical properties of friction stir welded (FSW) aluminium plates incorporating process parameters such as rotational speed and welding speed. In this work, two innovative methods such as response surface methodology and artificial neural network are used to predict the tensile strength of friction stir welded RDE-40 aluminium alloy.

II. EXPERIMENTAL WORK

A. Identifying the Important Parameters.

From the literature [9] and the previous work done [7,8] in our laboratory among the many independently controllable primary and secondary process parameters affecting the tensile strength, the primary process parameters viz rotational speed (N) and welding speed (S), and axial Force (F), were selected as process parameters for this study. The rotational speed (N) and welding speed (S), and axial force (F) are the primary parameters contributing to the heat input and subsequently influencing the tensile strength variations in the friction stir welded aluminium alloy joints.

B. Finding the Working Limits of Parameters

A large number of trial runs were carried out using 6 mm thick rolled plates of RDE-40 aluminium alloy to find out the feasible working limits of FSW process parameters. The chemical composition and mechanical properties of RDE-40 aluminium alloy are presented in Table 1. Different combinations of process parameters were used to carryout the trial runs. This was carried out by varying one of the factors while keeping the rest of them at constant values. The working range of each process parameter was decided upon by inspecting the macrostructure (cross section of weld) for a smooth appearance without any visible defects such as tunnel defect, pinhole, kissing bond, lazy S, etc. and presented in Table.2

C.Conducting the Experiments

The rolled plates of 6 mm were cut into the required sizes (300 mm x 150 mm) by power hacksaw cutting and milling. The design matrix chosen to conduct the experiments was a central composite face centered design, which is shown in Table 3. Square butt joint configuration was prepared to fabricate FSW joints. A non-consumable, rotating tool made of high carbon steel was used to fabricate FSW joints. An indigenously designed and developed machine (15 hp; 3000 rpm; 25 kN) was used to fabricate the joints. The welded joints were sliced using a power hacksaw and then machined to the required dimensions. American Society for Testing of Materials (ASTM E8M-04) guidelines was followed for preparing the test specimens. Three tensile specimens were prepared from each joint to evaluate the transverse tensile strength. Tensile test was carried out in 100 kN, electro-mechanical controlled Universal Testing Machine (Make: FIE-Bluestar, India; Model: UNITEK-94100) and the average of the three results is presented in Table 3.

III. PREDICTION OF TENSILE STRENGTH

A. Mathematical Model by Response Surface Methodology (RSM)

In practical applications of RSM, it is necessary to develop a fitting model for the response surface, and it is typically driven by some unknown physical mechanism. For prediction, the response surface method (RSM) is practical, economical and relatively easy for use [10]. In this present investigation, to correlate the process parameters and the tensile strength of friction stir welded RDE-40 joints; a second order quadratic model is developed to predict the tensile strength of friction stir welded RDE-40 joints based on experimentally measured tensile strength. Representing the tensile strength of the welded joints "TS", the response function can be expressed as TS = f (N, S, F). The model chosen includes the effects of main and interaction effect of all factors. The second order polynomial (regression) equation used to represent the response surface 'Y' is given by

$Y = b_0 + \Sigma\, b_i x_i + \Sigma\, b_{ii} x_i^2 + \Sigma\, b_{ij} x_i x_j + e_r$ and for three factors, the selected polynomial could be expressed as

$$TS=b_0+b_1(N)+b_2(S)+b_3(F)+b_{11}(N^2)+b_{22}(S^2)+b_{33}(F^2)+b_{12}(NS)+b_{13}(NF)+b_{23}(SF)$$

In order to estimate the regression coefficients, a number of experimental design techniques are available. In this work, central composite face centered design (Table 3) was used which fits the second order response surfaces very accurately. Central composite face centered (CCF) design matrix with the star points are at the center of each face of factorial space was used, so (γ = ± 1. This variety requires 3 levels of each factor. CCF designs provide relatively high quality predictions over the entire design space and do not require using points outside the original factor range. The upper limit of a factor was coded as +1, and the lower limit was coded as 1. All the coefficients were obtained applying central composite face centered design using the Design Expert statistical software package. After determining the significant coefficients (at 95% confidence level), the final model was developed using only these coefficients and the final mathematical model to estimate tensile strength is given below:

$$\text{Tensile strength (TS)} = \{311.44 + 16.50\,(N) - 5.30\,(S) + 5.00\,(F) - 4.50\,(NS) - 8.75(NF) + 4.50(SF) - 35.59\,N^2 - 58.59\,S^2 - 12.09F^2\}$$

B.1. Checking the Adequacy of Model

The adequacy of the developed model was tested using the analysis of variance (ANOVA) technique and the results of second order response surface model fitting in the form of analysis of variance (ANOVA) are given in Table 4. The determination coefficient (R^2) indicates the goodness of fit for the model. In this case, the value of the determination coefficient (R^2 = 0.96998) indicates that only 3% of the total variations are not explained by the model. The value of adjusted determination coefficient (adjusted R^2 = 0.9539) is also high, which indicates a high significance of the model. Predicted R^2 is also made a good agreement with the adjusted R^2. The value of probability > F in Table 4 for model is less than 0.05, which indicates that the model is significant. In the same way, rotational speed (N), welding speed (S) and axial force (F), interaction effect of rotational speed with welding speed, interaction effect of rotational speed with axial force (NF), interaction effect of welding speed with axial force (SF) and second order term of rotational speed (N), welding speed (S) and axial force (F) have significant effect. Lack of fit is non significant as it is desired [11]. All the above consideration indicates an excellent adequacy of the regression model.

C. Artificial Neural Network (ANN)

ANNs are computational models, which replicate the function of a biological network, composed of neurons and are used to solve complex functions in various applications. Neural networks consist of simple synchronous processing elements that are inspired by the biological nerve systems. The basic unit in the ANN is the neuron. Neurons are connected to each other by links known as synapses; associated with each synapse there is a weight factor. Details on the neural network modeling approach are given in else where [13].One of the most popular learning-algorithms is the back-propagation (BP) algorithm. In this present study, BP algorithm is used with a single hidden layer improved with numerical optimization techniques called Levenberg- Marquardt (LM) [14].The architecture of ANN used in this study is 3-12$_1$-1, 3 corresponding to the input values, 12 to the number of hidden layer neurons and 1 to the output. The topology architecture of feed-forward three-layered back propagation neural network is illustrated in Fig.1. MATLAB 7.1 has been used for training the network model for tensile strength prediction. The training parameters used in this investigation are shown in Table.5 The neural network described in this paper, after successful training, will be used to predict the tensile strength of friction stir welded joints of RDE-40 aluminium alloy within the trained range. Statistical methods were used to compare the results produced by the network. Errors occurring at the learning and testing stages are called the root-mean squared (RMS), absolute fraction of variance (R^2), and mean error percentage values. These are defined as follows, respectively:

$$\mathrm{RMS} = \left((1/p)\sum |tj - oj|^2\right)^{1/2},$$

$$R^2 = 1 - \left(\frac{\sum_j (tj - oj)^2}{\sum_j (oj)^2}\right),$$

$$\text{mean error} = \frac{1}{p}\sum_j \left(\frac{tj - oj}{tj}100\right).$$

Where, p no of patterns, t_j Target tensile strength, o_j Actual tensile strength

IV. COMPARISON OF ANN AND RS MODELS

The trend in the modelling using RSM has a low order non-linear behaviour with a regular experimental domain and relatively small factors region, due to its limitation in building a model to fit the data over an irregular experimental region. Moreover, the main advantage of RSM is its ability to exhibit the factor contributions from the coefficients in the regression model. This ability is powerful in identifying the insignificant main factors and interactions factors or insignificant quadratic terms in the model and thereby can reduce the complexity of the problem. On the other hand, this technique required good definition of ranges for each factor to ensure that the response(s) under consideration is changing in a regular manner within this range. It noted that ANNs perform better than the other techniques, especially RSM when highly non-linear behaviour is the case. Also, this technique can build an efficient model using a small number of experiments; however the technique accuracy would be better when a larger number of experiments are used to develop a model. On the other hand, the ANN model itself provides little information about the design factors and their contribution to the response if further analysis has not been done. Generation of ANN model requires a large number of iterative calculations whereas it is only a single step calculation for a response surface model. Depending of the nonlinearity of the problem and the number of parameters, an ANN model may require a high computational cost to create. Although computationally much more costly than a response model, ANN model led to comparatively accurate tensile strength predictions as shown in Table.6. The mean errors for ANN and RS model are about 0.258847% and 0.769831% respectively. The error against observation order of both the models is compared in Fig.2.

V. CONCLUSIONS

This paper has described the use of Design of Experiments (DOE) for conducting experiments. Two innovative models, response surface and artificial neural network (ANN), for predicting tensile strength of friction stir welded RDE-40 aluminium alloy. From this investigation, following important conclusions are derived.

(1) A mathematical model has been developed to predict the tensile strength of friction stir welded RDE-40 aluminium alloy joints at 95% confidence level, incorporating FSW process parameters.

(2) The predictive ANN model is found to be capable of better predictions of tensile strength within the range that they had been trained. The results of the ANN model indicate it to be much more robust and accurate in estimating the values of tensile strength when compared with the response surface model.

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Table 1(a) Chemical composition (wt %) of base metal

Zn	*Mg*	*Mn*	*Fe*	*Si*	*Cu*	*Cr*	*Ti*	*Al*
3.62	**2.49**	**0.18**	**0.28**	**-**	**0.1**	**-**	**-**	**Bal**

Table 1(b) Mechanical properties of base metal

Yield Strength (MPa)	***Ultimate Tensile Strength (MPa)***	***Elongation (%)***	***Reduction in cross sectional area (%)***	***Hardness (VHN)***
304	383	15.0	10.25	130

Table 2 Important factors and their levels for RDE-40 aluminum alloy

#	Parameter	Notation	Unit	Levels (-1)	Levels (0)	Levels (+1)
1	Rotational Speed	N	rpm	1200	1400	1600
2	Welding Speed	S	mm/min	22	45	75
3.	Axial Force	F	kN	4	6	8

Table 3 Experimental design matrix and results

Std	Run	Coded values			Real values			Tensile strength of the joint (MPa)
		N	S	F	Rotational speed (rpm)	Welding speed (mm/min)	Axial force (kN)	
1	15	-1	-1	-1	1200	22	4	180
2	9	+1	-1	-1	1600	22	4	238
3	8	-1	+1	-1	1200	75	4	170
4	7	+1	+1	-1	1600	75	4	211
5	10	-1	-1	+1	1200	22	8	200
6	18	+1	-1	+1	1600	22	8	224
7	5	-1	+1	+1	1200	75	8	209
8	17	+1	+1	+1	1600	75	8	214
9	1	-1	0	0	1200	45	6	255
10	16	+1	0	0	1600	45	6	292
11	11	0	-1	0	1400	22	6	258
12	12	0	+1	0	1400	75	6	243
13	3	0	0	-1	1400	45	4	296
14	20	0	0	+1	1400	45	8	298
15	2	0	0	0	1400	45	6	317
16	13	0	0	0	1400	45	6	315
17	4	0	0	0	1400	45	6	309
18	14	0	0	0	1400	45	6	311
19	6	0	0	0	1400	45	6	312
20	19	0	0	0	1400	45	6	314

Table 4 ANOVA results for tensile strength (Only significant terms).

Source	Sum of squares	df	Mean square	F Value	p-value Prob>F
Model	44763.17	9	5307.02	342.33	<0.0001
N-Rotational speed	2722.50	1	2722.50	175.61	<0.0001
S-Welding speed	280.90	1	280.90	18.12	0.0017

Axial force	250.00	1	250.00	16.13	0.0025
AB	162.00	1	162.00	10.45	0.0090
AC	612.50	1	612.50	39.51	<0.0001
BC	162.00	1	162.00	10.45	0.0090
A^2	3483.46	1	3483.46	224.70	<0.0001
B^2	9440.46	1	9440.46	608.95	<0.0001
C^2	402.02	1	402.02	25.93	0.0005
Residual	155.03	10	15.50		
Lack of Fit	113.03	5	22.61	2.69	0.1506
Cor.Total	47918.20	19			

Table 5 Training parameters used

.Number of Input nodes	3
Number of hidden nodes (feed forward)	11
Number of output nodes	1
Learning rule	Levenburg marquatt
No of epochs	500
Mu	0.01

Table 6 Comparison between RSM and ANN

Model summary and prediction errors	**Response surface methodology (RSM)**	**Artificial neural network (ANN)**
Root mean square(RMS)	2.784724	1.454125
R^2	0.969978	0.991814
Mean % Error	0.769831	0.258847
Computational time	Short	Long
Experimental domain	Regular	Irregular or regular
Model developing	With interactions	No interactions
Understanding	Easy	Moderate
Application	Frequently	Frequently