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Comparison of RSM with ANN in predicting tensile strength of friction stir welded AA7039 aluminium alloy joints

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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, play a major role in deciding the weld quality. Two methods, response surface methodology and artificial neural network were used to predict the tensile strength of friction stir welded AA7039 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 was developed. Sensitivity analysis was carried out to identify critical parameters. The results obtained through response surface methodology were compared with those through artificial neural networks.

Key words: friction stir welding; aluminium alloy; tensile strength; response surface methodology; artificial neural network

1 Introduction

FSW is an innovative solid state joining process in which the material that is being welded does not melt and recast[1]. Due to the absence of parent metal melting, the FSW process is observed to offer several advantages over fusion welding such as no problems of solidification cracks and porosity. Moreover, this technique is useful to join high strength aluminium alloys especially 2××× and 7××× which were considered unweldable by conventional fusion welding processes[2]. To obtain the desired strength, it is essential to have a complete control over the relevant process parameters to maximize the tensile strength on which the quality of a weldment is based. Therefore, it is very important to select and control the welding process parameters for obtaining the maximum strength. 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. The response surface methodology(RSM) is helpful in developing a suitable approximation for the true functional relationship between the independent variables and the response variable that may characterize the nature of the joints[3]. It has been proved by several researchers[4−7] that efficient use of statistical design of experimental techniques, allows development of an empirical methodology, to incorporate a scientific approach in the fusion welding procedure.

Recently, in the fields of materials joining, computer aided artificial neural network(ANN) modeling has gained increased importance. DUTTA et al[8] modeled the gas tungsten arc welding process using conventional regression analysis and neural network-based approaches and found that the performance of ANN was better compared with regression analysis. ATES et al[9] presented the use of artificial neural network for prediction of gas metal arc welding parameters. OKUYUCU et al[10] 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.

Even though sufficient literature is available on friction stir welding of aluminium alloys, no systematic study has been reported so far to correlate the process parameters and tensile properties of friction stir welded aluminium alloy joints. Hence, in this investigation, the design was used to conduct the experiments for exploring

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the interdependence of the process parameters and second order quadratic model for the prediction of tensile strength was developed from the data obtained by conducting the experiments. The results obtained through response methodology are compared with those through artificial neural network.

2 Experimental

2.1 Identifying important parameters

From the literature[11] and the previous work [12−13] done in our laboratory, among many independently controllable primary and secondary process parameters (as shown in Fig.1) affecting the tensile strength, the primary process parameters viz rotational speed(N), welding speed(S), and axial force (F), were selected as process parameters for this study. The rotational speed(N), 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.

2.2 Finding working limits of parameters

A large number of trial runs were carried out using 6 mm-thick rolled plates of AA7039 aluminium alloy to find out the feasible working limits of FSW process parameters. The chemical composition and mechanical properties of AA7039 aluminium alloy are presented in Tables 1 and 2. Different combinations of process parameters were used to carry out 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. From the above inspection, the following observations were made:

Table 1 Chemical composition of base metal (mass fraction, %)

Zn	Mg	Mn	Fe	Si	Cu	Cr	Ti	Al
3.62	2.49	0.18	0.28	−	0.1	−	−	Bal.

Table 2 Mechanical properties of base metal

Yield strength/MPa	Ultimate tensile strength/MPa	Elongation/%	Reduction in cross sectional area/%	Hardness (Hv)
304	383	15.0	10.25	130

1) When the rotational speed was lower than 1 200 r/min, wormhole at the retreating side of weld nugget was observed (Fig.2(a)) and it may be due to insufficient heat generation and insufficient metal transportation; on the other hand, when the rotational speed was higher than 1 600 r/min, tunnel defect was observed (Fig.2(b)) and it may be due to excessive turbulence caused by higher rotational speed.

2) Similarly, when the welding speed was lower than 22 mm/min, pin holes type of defect was observed (Fig.2(c)) due to excessive heat input per unit length of the weld and no vertical movement of the metal; when the welding speed was higher than 75 mm/min, tunnel at the bottom in retreating side was observed (Fig.2(d)) due to inadequate flow of material caused by insufficient heat input.

3) When the axial force was lower than 4 kN, tunnel and crack like defect at the middle of the weld cross section on retreating side was observed (Fig.2(e)) due to the absence of vertical flow of material caused by insufficient downward force; when the axial force was increased beyond 8 kN, a large mass of flash and excessive thinning was observed (Fig.2(f)) due to higher heat input.

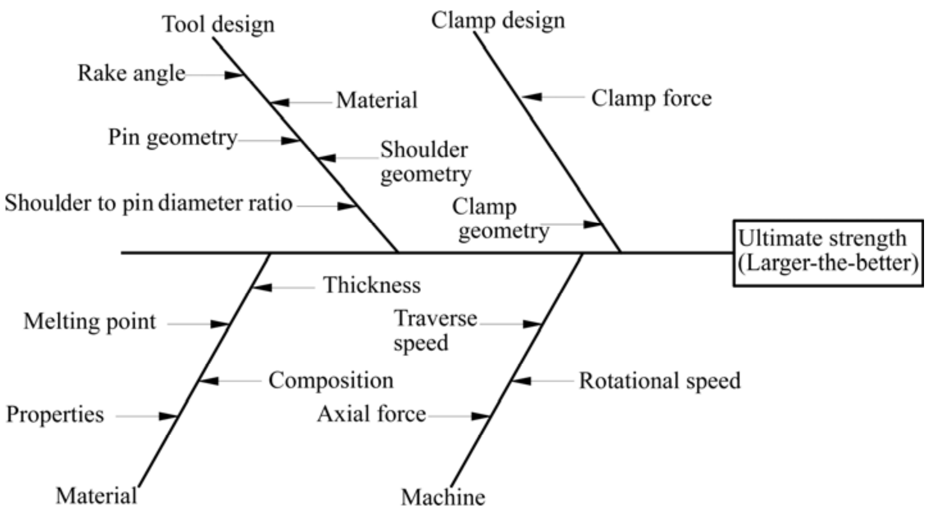

Fig.1 Cause and effect diagram

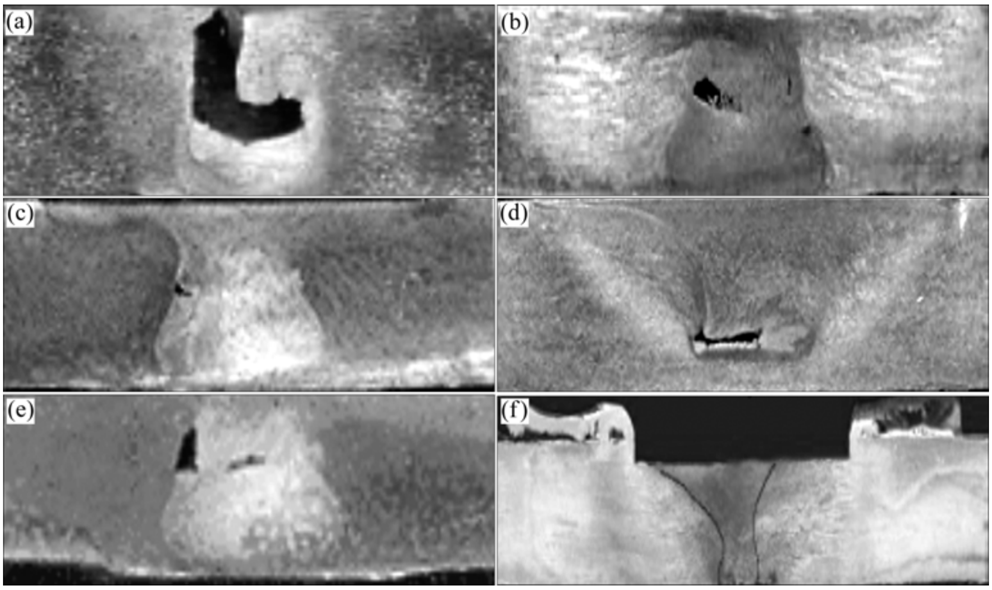

Fig.2 Cross sectional macrostructures of joints: (a) 1 100 r/min; (b) 1 700 r/min; (c) 15 mm/min; (d) 100 mm/min; (e) 3 kN; (f) 9 kN

The chosen levels of the selected process parameters with their units and notations are presented in Table 3.

Table 3 Important FSW process parameters and their levels for AA7039 aluminum alloy

Parameter	Level		
	(−1)	(0)	(+1)
Rotational speed, $N/(\mathrm{r \cdot min^{-1}})$	1 200	1 400	1 600
Welding speed, $S/(\mathrm{mm \cdot min^{-1}})$	22	45	75
Axial force, F/kN	4	6	8

2.3 Conducting experiments

The rolled plates of 6 mm in thickness were cut into the required sizes (300 mm × 100 mm) by power hacksaw cutting and milling. The design matrix chosen to conduct the experiments was a central composite face centered design, which is listed in Table 4. 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; 3 000 r/min; 25 kN) was used to fabricate the joints. The welded joints were sliced (as shown in Fig.3(a)) using a power hacksaw and then machined to the required dimensions as shown in Fig.3(b). American Society for Testing of Materials (ASTM E8M-04) guidelines were 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 (Maker: FIE-Bluestar, India; Model: UNITEK−94100) and the average of the three results is presented in Table 4.

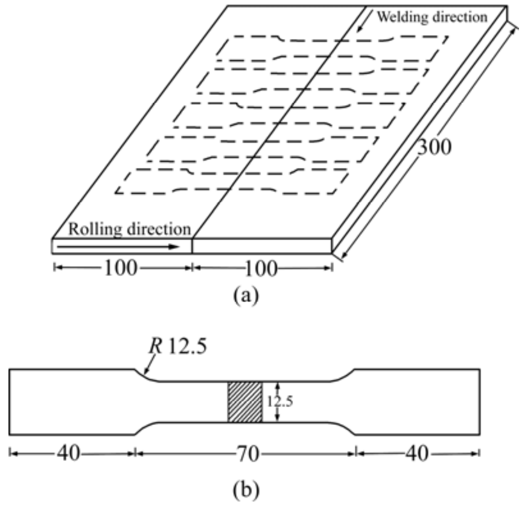

Fig.3 Scheme of welding with respect to rolling direction and extraction of tensile specimens (a) and dimensions of flat tensile specimen (b) (unit: mm)

3 Development of mathematical model

3.1 Response surface methodology

Response surface methodology(RSM) is a collection of mathematical and statistical technique useful for analyzing problems in which several independent variables influence a dependent variable or response and the goal is to optimize the response[14]. In many experimental conditions, it is possible to represent independent factors in quantitative form as given in Eq.(1). Then these factors can be thought of as having a functional relationship or response as follows:

$$Y=\Phi(x_1, x_2, \cdots, x_k)\pm e_\mathrm{r} \tag{1}$$

Between the response Y and x_1, x_2, $\cdots$, x_k of k quantitative factors, the function Φ is called response

Table 4 Experimental design matrix and results

Std	Run	Coded value			Real value			Tensile strength/MPa
		N	S	F	Rotational speed/(r·min^{-1})	Welding speed/(mm·min^{-1})	Axial force/kN	
1	15	−1	−1	−1	1 200	22	4	180
2	9	+1	−1	−1	1 600	22	4	238
3	8	−1	+1	−1	1 200	75	4	170
4	7	+1	+1	−1	1 600	75	4	211
5	10	−1	−1	+1	1 200	22	8	200
6	18	+1	−1	+1	1 600	22	8	224
7	5	−1	+1	+1	1 200	75	8	209
8	17	+1	+1	+1	1 600	75	8	214
9	1	−1	0	0	1 200	45	6	255
10	16	+1	0	0	1 600	45	6	292
11	11	0	−1	0	1 400	22	6	258
12	12	0	+1	0	1 400	75	6	243
13	3	0	0	−1	1 400	45	4	296
14	20	0	0	+1	1 400	45	8	298
15	2	0	0	0	1 400	45	6	317
16	13	0	0	0	1 400	45	6	315
17	4	0	0	0	1 400	45	6	309
18	14	0	0	0	1 400	45	6	311
19	6	0	0	0	1 400	45	6	312
20	19	0	0	0	1 400	45	6	314

surface or response function. The residual e_{r} measures the experimental errors. For a given set of independent variables, a characteristic surface is responded. When the mathematical form of Φ is not known, it can be approximate satisfactorily within the experimental region by polynomial. In the present investigation, RSM has been applied for developing the mathematical model in the form of multiple regression equations for the quality characteristic of the friction stir welded AA7039 aluminium alloy. In applying the response surface methodology, the independent variable was viewed as a surface to which a mathematical model is fitted.

The second order polynomial (regression) equation used to represent the response surface Y is given by[15]

$$Y = b_0 + \sum b_i x_i + \sum b_{ii} x_i^2 + \sum b_{ij} x_i x_j + e_{\mathrm{r}} \tag{2}$$

and for three factors, the selected polynomial could be expressed as

$$\sigma=b_0+b_1(N)+b_2(S)+b_3(F)+b_{11}(N^2)+b_{22}(S^2)+b_{33}(F^2)+ b_{12}(NS)+b_{13}(NF)+b_{23}(SF) \tag{3}$$

In order to estimate the regression coefficients, a number of experimental design techniques are available. In this work, central composite face centered design (Table 4) was used which fits the second order response surfaces very accurately. Central composite face centered (CCF) design matrix with the star points being at the center of each face of factorial space was used, so $\alpha=\pm1$. This variety requires three 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:

$$\text{Tensile strength}(\sigma)=\{311.44+16.50(N)-5.30(S)+5.00(F)- 4.50(NS)-8.75(NF)+4.50(SF)-35.59N^2- 58.59S^2-12.09F^2 \tag{4}$$

3.2 Checking 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 5. The determination coefficient(R^2) indicates

Table 5 ANOVA results for tensile strength (only significant terms)

Source	Sum of squares	df	Mean square	F value	p-value probability$>F$
Model	44 763.17	9	5 307.02	342.33	$<$0.000 1
Rotational speed, N	2 722.50	1	2 722.50	175.61	$<$0.000 1
Welding speed, S	280.90	1	280.90	18.12	0.001 7
Axial force, F	250.00	1	250.00	16.13	0.002 5
NS	162.00	1	162.00	10.45	0.009 0
NF	612.50	1	612.50	39.51	$<$0.000 1
SF	162.00	1	162.00	10.45	0.009 0
N^2	3 483.46	1	3 483.46	224.70	$<$0.000 1
S^2	9 440.46	1	9 440.46	608.95	$<$0.000 1
F^2	402.02	1	402.02	25.93	0.000 5
Residual	155.03	10	15.50		
Lack of fit	113.03	5	22.61	2.69	0.150 6
Pure error	42.00	5	8.40		
Corrected total	47 918.20	19			
Standard deviation	3.94		R^2=0.969 9		
Mean	258.85		Adjusted R^2=0.953 9		
Coefficient of variation	1.52		Predicted R^2=0.952 2		
Press	758.28		Adequate R^2=50.94 0		

the goodness of fit for the model. In this case, the value of the determination coefficient (R^2=0.969 98) indicates that only less than 3% of the total variations are not explained by the model. The value of adjusted determination coefficient (adjusted R^2=0.953 9) is also high, which indicates a high significance of the model. Predicted R^2 is also in a good agreement with the adjusted R^2. Adequate precision compares the range of predicted values at the design points to the average prediction error. At the same time a relatively lower value of the coefficient of variation (CV=1.52) indicates improved precision and reliability of the conducted experiments.

The value of probability $>F$ in Table 5 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. The normal probability plot of the residuals for tensile strength shown in Fig.4 reveals that the residuals are falling on the straight line, which means the errors are distributed normally[16]. All the above consideration indicates an excellent adequacy of the regression model. Each observed value is compared with the predicted value calculated from the model in Fig.5.

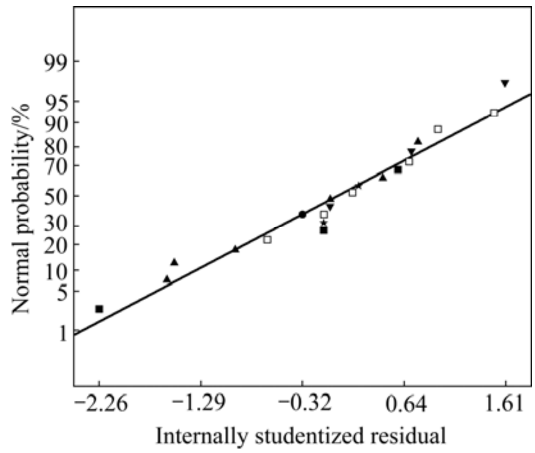

Fig.4 Normal probability plot of residuals for tensile strength

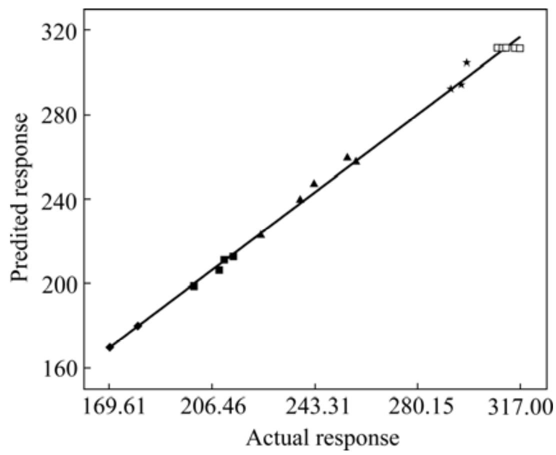

Fig.5 Plot of actual vs predicted response of tensile strength

3.3 Optimising parameters

Contour plots show distinctive circular shape indicative of possible independence of factors with response. A contour plot is produced to visually display the region of optimal factor settings. For second order response surfaces, such a plot can be more complex than the simple series of parallel lines that can occur with first order models. Once the stationary point is found, it is usually necessary to characterize the response surface in the immediate vicinity of the point by identifying whether the stationary point found is a maximum response or minimum response or a saddle point. To classify this, the most straightforward way is to examine through a contour plot. Contour plots play a very important role in the study of the response surface. By generating contour plots using software for response surface analysis, the optimum is located with reasonable accuracy by characterizing the shape of the surface. If a contour patterning of circular shaped contours occurs, it tends to suggest independence of factor effects while elliptical contours as may indicate factor interactions[17]. Response surfaces have been developed for both the models, taking two parameters in the middle level and two parameters in the *X* and *Y* axis and response in *Z* axis. The response surfaces clearly reveal the optimal response point. RSM is used to find the optimal set of process parameters that produce a maximum or minimum value of the response[18]. In the present investigation the process parameters corresponding to the maximum tensile strength are considered as optimum (analyzing the contour graphs and by solving Eq.(4)). Hence, when these optimized process parameters are used, then it will be possible to attain the maximum tensile strength.

Fig.6 presents three dimensional response surface plots for the response tensile strength obtained from the regression model. The optimum tensile strength is exhibited by the apex of the response surface. Fig.7(a) exhibits almost a circular contour, which suggests independence of factor effect namely rotational speed. It is relatively easy by examining the contour plots (Figs.7(b) and 7(c)), that changes in the tensile strength are more sensitive to changes in rotational speed than to changes in welding speed and axial force. When welding speed is compared with axial force at a constant rotational speed of 1 400 r/min, welding speed force is slightly more sensitive to changes in tensile strength as illustrated in contour plot (Fig.7(c)). Interaction effect between the factors rotational speed and welding speed, rotational speed and axial force, and welding speed and axial force on tensile strength also exists, which is evidenced from the contour plot. Increase in rotational speed resulted in drop in initial axial force with increasing time[19]. The interaction effect between rotational speed and axial force has more significance than

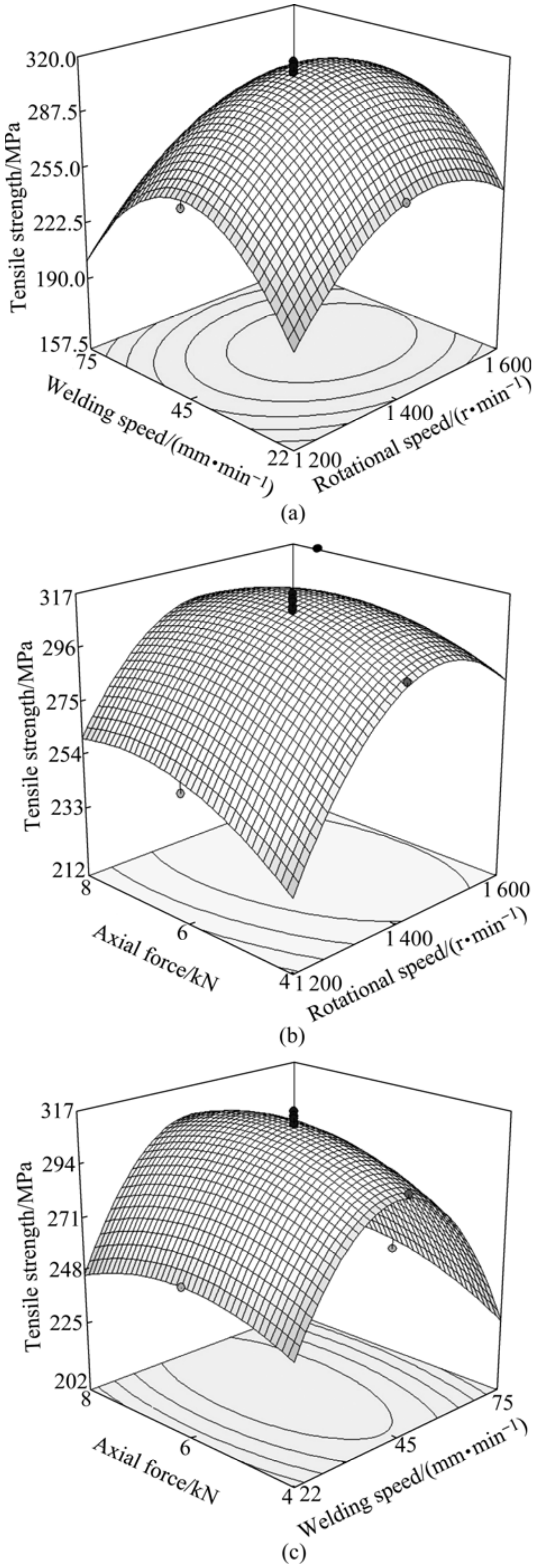

Fig.6 Response plots of process parameters on tensile strength

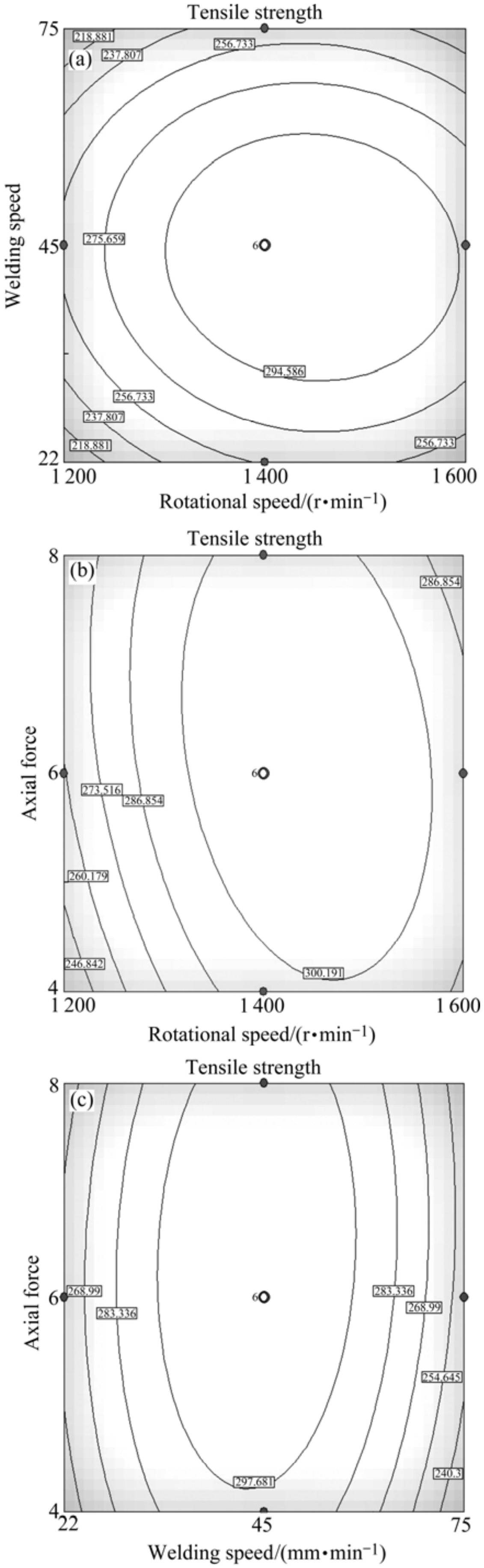

Fig.7 Contour plots of process parameters on tensile strength

the interaction effect between rotational speed and welding speed, welding speed and axial force. Predicted optimum tensile strength obtained from the response surface and contour plots by using a rotational speed of 1 460 r/min, welding speed of 40 mm/min, and axial force of 6.5 kN is 311 MPa. To demonstrate the validity of the model, three experiments were conducted at the optimum values of process parameters and average tensile strength of friction stir welded AA7039 aluminium alloy was found to be 319 MPa, which shows the excellent agreement with the predicted values.

3.4 Sensitivity analysis

Sensitivity analysis, a method to identify critical parameters and rank them by their order of importance, is paramount in model validation where attempts are made to compare the calculated output to the measured data. This type of analysis can study which parameter must be most accurately measured, thus determining the input parameters exerting the most influence upon model outputs[20]. Mathematically, sensitivity of a design objective function with respect to a design variable is the partial derivative of that function with respect to its variables. To obtain the sensitivity equation for rotational speed, Eq.(4) is differentiated with respect to rotational speed. The sensitivity equations (5), (6) and (7) represent the sensitivity of tensile strength for rotational speed, welding speed and axial force, respectively.

$$\frac{\partial\sigma}{\partial N}=16.56-4.5S-8.75F-71.18N \tag{5}$$

$$\frac{\partial\sigma}{\partial S}=-5.30-4.5N-4.5F-117.18S \tag{6}$$

$$\frac{\partial\sigma}{\partial F}=5.00-8.75N-4.5S-24.18S \tag{7}$$

In this study, it is aimed to predict the tendency of tensile strength due to a small change in process parameters for FSW process. Sensitivity information should be interpreted using mathematical definition of derivatives. Namely, positive sensitivity values imply an increment in the objective function by a small change in design parameter whereas negative values state the opposite[21]. Sensitivities of process parameters on tensile strength are presented in Table 6. Fig.8 shows the sensitivity of rotational speed, welding speed and axial force respectively on tensile strength. The small variation of rotational speed causes large changes in tensile strength when the speed increases. The results reveal that the tensile strength is more sensitive to rotational speed than welding speed and axial force.

Table 6 Tensile strength sensitivities of process parameters (S=45 mm/min)

Axial force/kN	Rotational speed/($r \cdot min^{-1}$)	Tensile strength/MPa	Sensitivity		
			$\partial\sigma/\partial N$	$\partial\sigma/\partial S$	$\partial\sigma/\partial F$
4	1 200	215	96.43	3.7	37.93
	1 400	296	25.25	−0.8	29.18
	1 600	269	−45.93	−5.3	20.43
6	1 200	255	87.68	−0.8	13.75
	1 400	317	16.5	−5.3	5.00
	1 600	292	−54.68	−9.8	−3.75
8	1 200	246	78.93	−5.3	−10.43
	1 400	298	7.75	−9.8	19.18
	1 600	266	−63.43	−14.3	−27.93

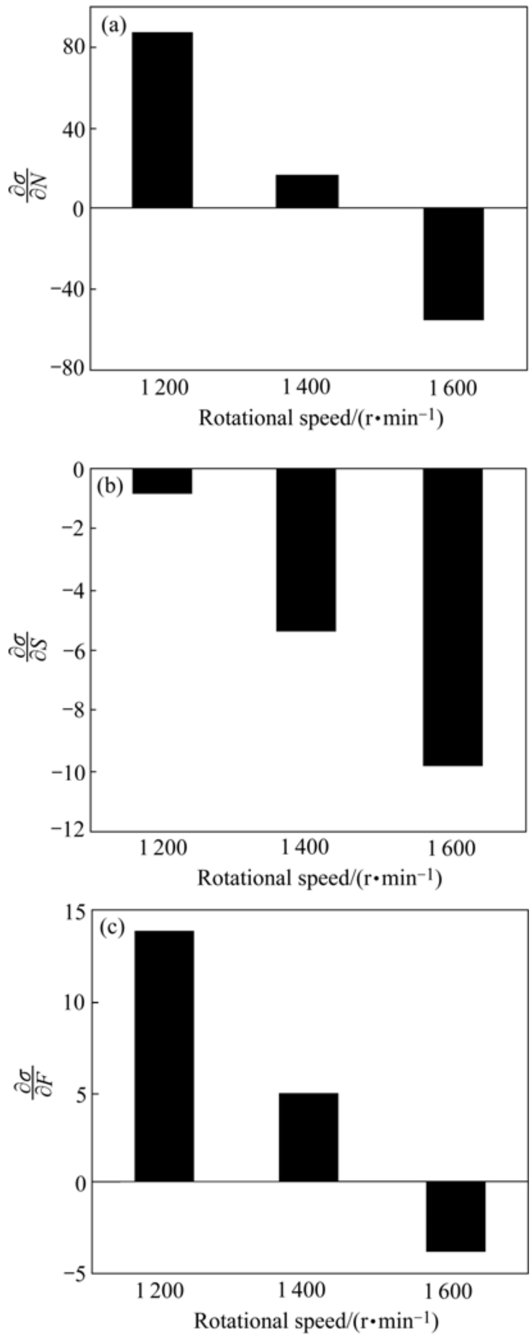

Fig.8 Sensitivity analysis result: (a) Rotational speed (N); (b) Welding speed (S); (c) Axial force (F)

4 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 elsewhere[22]. One of the most popular learning-algorithms is the back-propagation(BP) algorithm. In this present study, BP algorithm was used with a single hidden layer improved with numerical optimization techniques called Levenberg-Marquardt (LM)[23]. The architecture of ANN used in this study is 3-12_1-1, with 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.9. MATLAB 7.1 was used for training the network model for tensile strength prediction. The training parameters used in this investigation are listed in Table 7. The neural network described in this work, after successful training, was used to predict the tensile strength of friction stir welded joints of AA7039 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 square(RMS), absolute fraction of variance (R^2), and mean error percentage values. These are defined as follows, respectively:

$$\mathrm{RMS}=\left[(1/p)\sum\left|t_j-o_j\right|^2\right]^{1/2} \tag{8}$$

$$R^2=1-\left[\frac{\sum_j (t_j-o_j)^2}{\sum_j (o_j)^2}\right]^{1/2} \tag{9}$$

Table 7 Training parameters used

Parameter	Value
Number of input nodes	3
Number of hidden nodes (feed forward)	11
Number of output nodes	1
Learning rule	Levenburg-Marquatt
Number of epochs	500
Error goal	1.0×10^{-4}
Mu	0.01
Number of training sets used	1

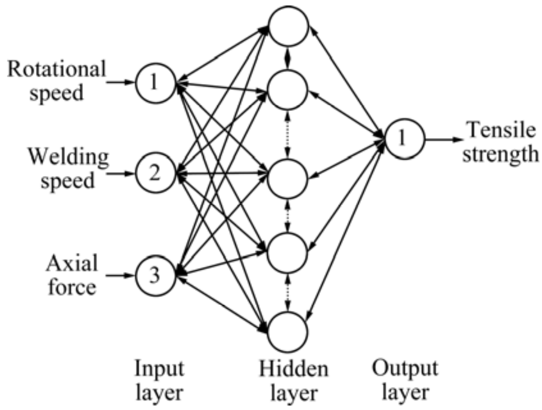

Fig.9 ANN architecture used

$$\text{Mean error}=(1/p)\sum_{j}\frac{t_j-o_j}{t_j}\times 100 \tag{10}$$

where p is the number of patterns, t_j is the target tensile strength, o_j is the actual tensile strength.

5 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 interaction factors or insignificant quadratic terms in the model and thereby can reduce the complexity of the problem. On the other hand, this technique requires good definition of ranges for each factor to ensure that the response(s) under consideration changes in a regular manner within this range. It is 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 on 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 leads to comparatively accurate tensile strength predictions as shown in Table 8. The mean errors for ANN and RS models are about 0.258 847% and 0.769 831% respectively. The error against observation order of both the models is compared in Fig.10.

Table 8 Comparison between RSM and ANN

Model summary and prediction errors	Response surface methodology(RSM)	Artificial neural network(ANN)
Root mean square (RMS)	2.784 724	1.454 125
R^2	0.969 978	0.991 814
Mean error/%	0.769 831	0.258 847
Computational time	Short	Long
Experimental domain	Regular	Irregular or regular
Model developing	With interactions	No interactions
Understanding	Easy	Moderate
Application	Frequently	Frequently

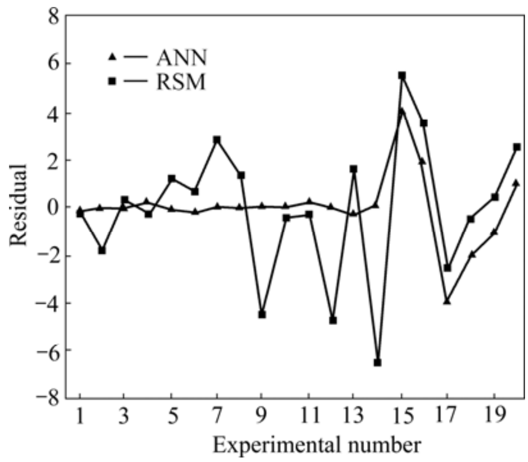

Fig.10 Comparison of observation order with residuals

6 Conclusions

This paper has described the use of design of experiments(DOE) for conducting experiments. Two models were developed for predicting tensile strength of friction stir welded AA7039 aluminium alloy using response surface methodology and artificial neural network(ANN). From this investigation, the following important conclusions are derived.

1) Rotational speed is the factor that has greater influence on tensile strength, followed by welding speed and axial force.

2) A maximum tensile strength of 319 MPa is exhibited by the FSW joints fabricated with the optimized parameters of 1 460 r/min rotational speed, 40 mm/min welding speed and 6.5 kN axial force.

3) 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 is much more robust and accurate in estimating the values of tensile strength when compared with the response surface model.

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