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Analysing the strength of friction stir spot welded joints of aluminium alloy by fuzzy logic

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Abstract. Friction stir spot welding (FSSW) is a recent joining technique developed for spot welding of thin metal sheets. This process currently finds application in automotive, aerospace, marine and sheet metal industry. In this work, the effect of FSSW process parameters namely tool rotation speed, shoulder diameter and dwell time on Tensile shear failure load (TSFL) is investigated. Box-Behnken design is selected for conducting experiments. Fuzzy based soft computing is used to develop a model for TSFL of AA6061 joints fabricated by FSSW. The interaction of the process parameters on TSFL is also presented.

1. Introduction

Aluminium alloys are widely used in aerospace and automobile industries because of attractive weight to density ratio. Conventional spot welding of aluminium alloys results in large heat distortion, poor weld joint strength and porosity defects. Friction stir spot welding (FSSW) is a new welding process that can be used to spot weld thin sheets of metals. Being solid state process, FSSW is more advantageous and overcomes the problems associated with fusion welding. It is considered as a potential replacement for conventional spot welding process and techniques [1].

The strength of joints fabricated by FSSW depends on process parameters, tool geometry, base material and the operating conditions like the temperature of the backing plate etc.[2,3]. Selection of the optimum parameters and operating conditions will yield joints with higher strengths. Karthikeyan and Balasubramanian [4] presented the effect of tool rotational speed, plunge rate, plunge depth, and dwell time on the strength of AA7075 joints obtained by FSSW. Lakshminarayana et al., [5] explored the interdependence of the process parameters when friction stir spot welding the low carbon steels in automotive applications. Patel et al., [6] investigated the effect of tool rotation on FSSW of AA5052-H32 and AA6082-T6 dissimilar aluminium alloys. Shin and Leon[7] discussed the failure load and fractography of aluminium and magnesium alloys joined by FSSW using tools without thread.

Bilici et al., [8] explored the effect of shoulder geometries, pin length, pin angle and concavity angle in addition to tool properties on static strength in friction stir spot welds of polyethylene sheets. Klobcar et al [9] friction stir spot welded AA 5754 in the lap configuration and analyzed the effect of FSSW process parameters on the strength of the joints. Rao et al [10] presented the influence of tool rotation rate and shoulder plunge depth on lap-shear failure load of AM60B to 6022-T4 dissimilar joints fabricated by FSSW. Li et al., [11] reported that tool with a half-threaded pin induced low heat input and enhanced the material flow at the lap interface. Paidar et al., [12] presented the effect of FSSW parameters on the fracture mode of aluminum alloy 2024-T3 joints.

Cox, Gibson et al. [13] reported that the strength of friction stir spot welded joints produced at less number of tool rotations was higher, compared to the joints produced at more number of tool rotation speeds. Recently soft computing techniques have been successfully applied in various fields of engineering like design optimization, scheduling, intelligent manufacturing, process control etc. Roshan et al., [14] developed relationship between FSW process parameters and mechanical properties of the resulting joints using adaptive neuro-fuzzy inference systems (ANFIS). J Gokulachandran et al., [15] reported two soft computing techniques for predicting the remaining useful life of cutting tools.

Obtaining defect free joints with superior mechanical, corrosion and tribological properties is possible when optimum process parameters are used during FSSW. In this study, the process parameters effect on the strength of friction stir spot welded AA6061 joints, is examined using fuzzy logic.

2. Experimental work

2.1. Selection of factors and number of levels of process variables

The coalescence of metal or alloy greatly depends on the amount of heat generated by the tool. In FSSW, the contact of rotating tool with the work piece generates heat. This heat is proportional to the rotation speed, area of contact and period of contact of the tool with the work piece. So shoulder diameter (SD), tool rotational speed (TRS) and dwell time (DT) were selected as factors for experimental work and subsequently for the development of analytical model in this work. The three factors selected were varied at three levels for predicting the TSFL of FSSW aluminium alloy. The selected process variables, values, units and notations are given in the Table 1.

Table 1. Parameters adopted

Std.	Coded Value	Real Value		
		Shoulder Diameter (mm)	Tool Rotational Speed (rpm)	Dwell Time (s)
1	-1	15	750	30
2	0	18	1125	45
3	1	21	1500	60

2.2. Experimental Methodology

Figure 1. FSSW setup

AA6061 plates of size 100 x 50 x 5 mm were friction stir spot welded by CNC controlled vertical milling machine as shown in Figure 1**.** The FSSW was performed using a cylindrical tool which was made of high carbon steel with tapered and threaded pin profile.

FSSW trials were performed on the plates as per Box-Behnken design with the above discussed factors and process variables. The results obtained are given in Table 2.

Table 2. Experimental TSFL Value

Std.	Coded Value			Experimental TSFL N	Predicted TSFL N	Percentage error % E
	SD	TRS	DT			
1	-1	-1	0	3128.00	3120.00	0.256
2	-1	+1	0	3327.00	3320.00	0.210
3	+1	-1	0	3481.00	3480.00	0.029
4	+1	+1	0	3213.00	3210.00	0.093
5	-1	0	-1	3876.00	3870.00	0.155
6	-1	0	+1	3287.00	3280.00	0.213
7	+1	0	-1	3631.00	3630.00	0.028
8	+1	0	+1	3958.00	3950.00	0.202
9	0	-1	-1	2584.20	2580.00	0.163
10	0	-1	+1	2896.00	2890.00	0.207
11	0	+1	-1	3025.00	3020.00	0.165
12	0	+1	+1	2935.90	2930.00	0.201
13	0	0	0	2923.00	2920.00	0.103
14	0	0	0	2921.00	2920.00	0.034
15	0	0	0	2927.00	2920.00	0.239

3. Modelling

The amalgamation of neural network and fuzzy systems forms neuro fuzzy system in which the neural network algorithms are used to determine the parameters of fuzzy system. The three systems of neuro fuzzy systems are: Co-operative neuro fuzzy system, Concurrent neuro fuzzy system and Hybrid neuro fuzzy system. The details of this method is discussed elsewhere. [10] In this work, Hybrid neuro fuzzy system is used to predict the TSFL of friction stir spot welded AA6061 plates. Defuzzification is obtained by adaptive neuro fuzzy interference system (ANFIS). The architecture of ANFIS is given in Figure 2 and it is a Sugeno fuzzy model [14]. It is shown in Figure 3.The final fuzzy interference is optimized through artificial neural network training [15].

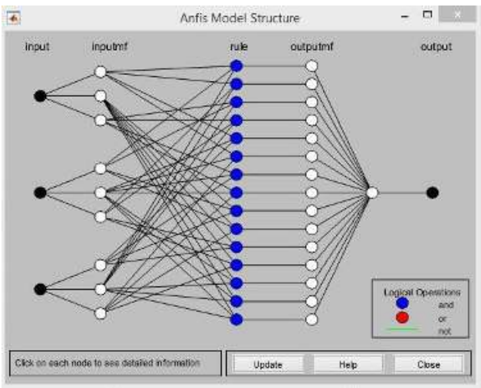

Figure 2. ANFIS architecture

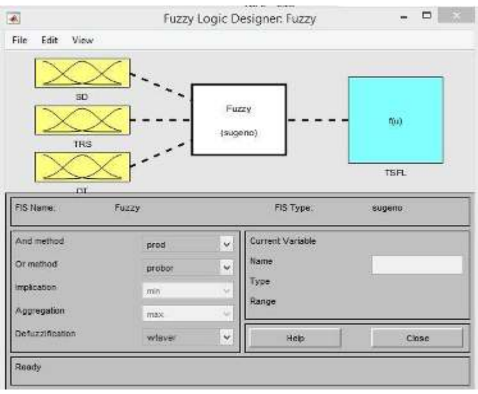

Figure 3. Sugeno-fuzzy model (MATLAB)

Here SD, TRS and DT were the input parameters to ANFIS. The output parameter for Sugeno fuzzy inference system was TSFL. The input and output parameters were converted to linguistic variables, fuzzy linguistic terms and membership functions. The linguistic variables low (l), medium (m) and high (h) were used for input parameters and very low (VL), low (L), medium (M), high (H) and very high (VH) for output parameter. Gaussian membership function ensures smooth boundaries for the invoke of fuzzy rules [13] & [14]. So it was chosen instead of triangular or trapezoidal membership functions. Three subsets were assigned to three inputs using MATLAB fuzzy tool box as shown in Figure 4, Figure 5 and Figure 6.

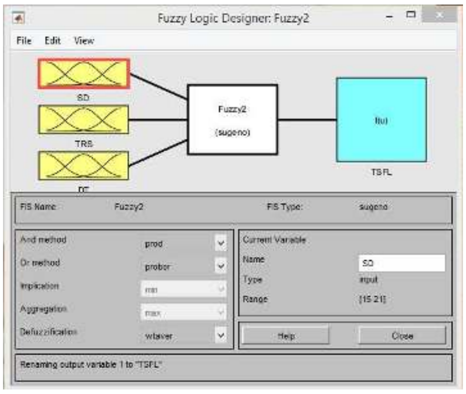

Figure 4. Gaussian membership function used for input variable 'SD'

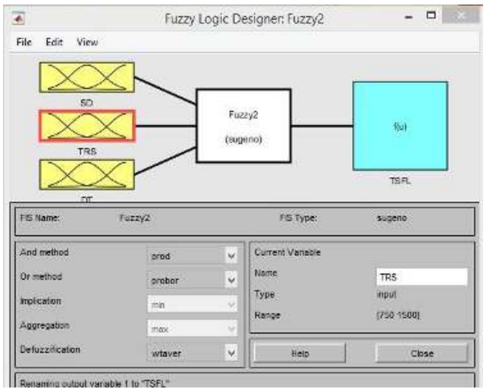

Figure 5. Gaussian membership function used for input variable 'TRS'

The fuzzy rule base with three parameters as input s_1, s_2, s_3 and one parameter t as output is show below.

Rule 1: if s_1 is A_1, s_2 is B_1 and s_3 is C_1 then t is $f_1(u)$

Rule 2: if s_1 is A_2, s_2 is B_2 and s_3 is C_2 then t is $f_2(u)$

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Rule n: if s_n is A_n, s_2 is B_n and s_3 is C_n then t is $f_n(u)$

A_i, B_i and C_i are the subsets defined by the analogous membership function and $f_i(u)$ is the crisp function. [12]

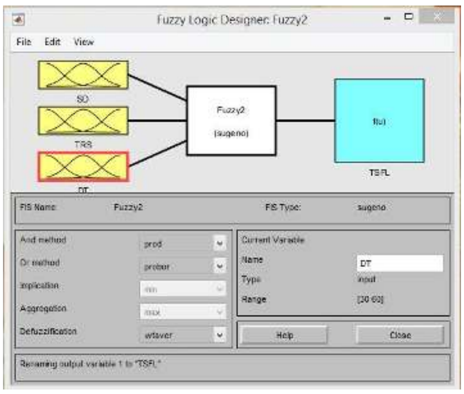

Figure 6. Gaussian membership function used for input variable 'DT'

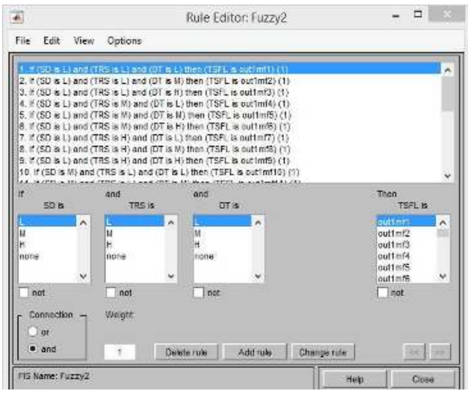

Figure 7. Rules fed to Sugeno fuzzy system

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Fuzzy rules were used to create relationship between the input parameters and the output parameter. The set of sixteen rules that relate the SD, TRS and DT with TSFL were shown in the Figure 7.

4. Results and Discussion

MATLAB fuzzy tool box was used to train the network model for predicting the TSFL of FSSW Aluminium plates. The parameters in tool box were set as follows. Optimization method – Hybrid; Error tolerance – 0.01; Epochs – 30. ANFIS was used to train the FIS to emulate the user defined training data by modifying the membership function parameters according to the error criterion. For training the network, 70% of measured data (TSFL) was used.

Model validation is the process of predicting the output values from the data that is not used to train the FIS. The first 15% of data was used for testing and the next 15% of data was used for checking. The model obtained was used to predict the TSFL values for the same set of process parameters.

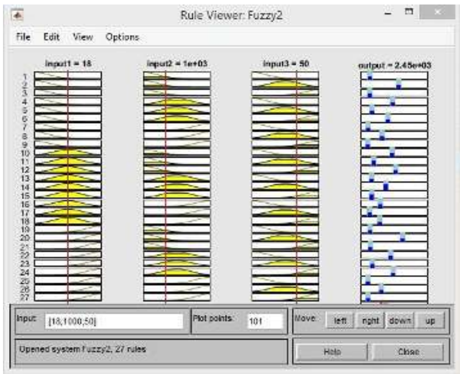

Figure 8. Rules viewer in fuzzy

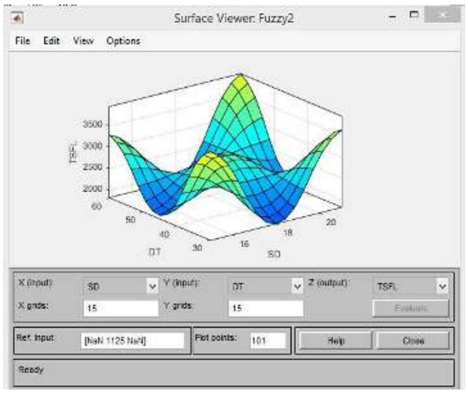

Figure 9. Interaction of DT and SD on TSFL plied to Sugeno fuzzy system

The fuzzy rule viewer is as shown in the Figure 8. It indicates the variation of response corresponding to the change in process parameters.

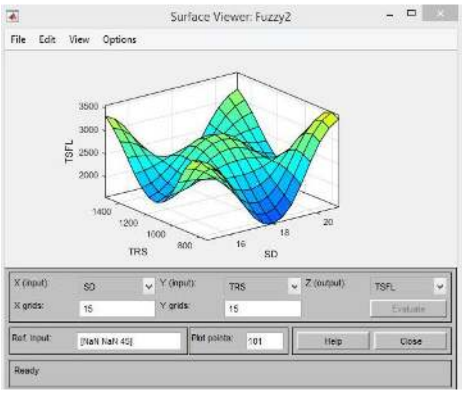

Figure 10. Interaction of TRS and SD on TSFL

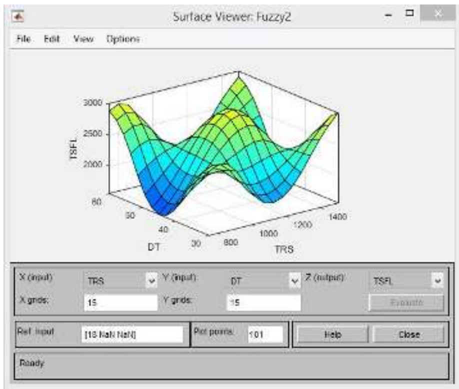

Figure 11. Interaction of DT and TRS on TSFL

The developed model was used to study the interaction of the process parameters for maximizing TSFL. Figure 9 shows the interaction of DT and SD. It is seen that maximum TSFL is obtained at high value of SD or with low value of SD and DT. Figure 10 shows the interaction of SD and TRS. It is observed that TSFL is maximized at high value of SD and TRS. The high surface area of welds with increased SD and TRS resulted in high TSFL. Figure 11 shows that the interaction of DT and TRS. It is perceived that the effect of TRS is highly sensible in maximizing TSFL compared with DT. Maximum TSFL is obtained at high value of TRS and low value of DT.

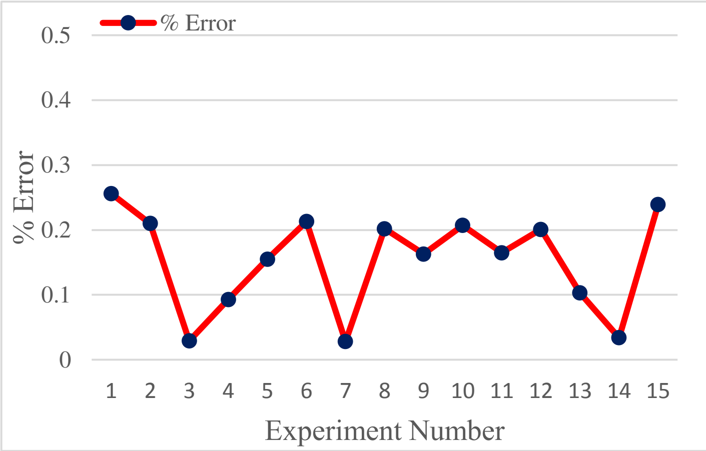

Figure 12. Error Prediction

The predicted values and percentage error between the predicted and experimental TSFL are given in Table 2. The percentage error between the experimental and predicted value is calculated using the Equation 1.

$$\%\ \text{Error} = \left(1 - \frac{Predicted\ Value}{Experimental\ Result}\right) * 100 \ \rightarrow (1)$$

The percentage error was a meagre quantity indicating the efficacy of the generated model. The Figure 12 shows the error value between the predicted and experimental value. Hence it is authenticated that the training data presented to ANFIS for training membership parameters is completely representing the data features of the intended model.

5. Conclusion

AA6061 was successfully friction stir spot welded using a vertical milling center by varying the process parameters. The TSFL of the joints were measured experimentally. Maximum TSFL of 3958 N was obtained at SD of 21 mm, TRS of 1125 rpm and DT of 60 s. Hybrid neuro fuzzy system was used to generate the model for predicting and studying the effect of process parameters on TSFL of joints obtained by friction stir spot welding. The experimental TSFL values were used to develop the fuzzy model for the prediction of TSFL. The methodology given in this paper delivers a useful tool assess the TSFL of FSSW AA6061. It is established that the developed predictive neuro fuzzy model gives better prediction of TSFL of the FSSW Aluminium alloy. The generated model can be used as an analysis tool in predicting the tensile shear failure load of FSSW joints of Aluminium alloy 6061.

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