Tensile shear strength and elongation of FSW parts predicted by Taguchi-based fuzzy logic

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Article Information

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This paper represents the fuzzy logic model for modeling and prediction of tensile shear strength and percent elongation of parts produced by the friction stir welding (FSW) process. A Taguchi L_{16} orthogonal array is used to plan and select the parameters and their levels. Weld travel speed, pin diameter and tool rotation are used as input variables. Therefore, a three-input and two-output fuzzy model is used to correlate these variables to the responses of tensile shear strength and percent elongation using the fuzzy rules generated based on experimental results. Close agreement is obtained between the fuzzy predicted and experimental results with the correlation coefficients of 0.931 and 0.895 for tensile shear strength and elongation, respectively.

Friction stir welding (FSW) is one of the most important welding techniques and it has been widely used in the area of space, aircraft, marine, fuel tank and food saving industry for about a decade. It has been used to weld Al alloys as well as Cu alloys, steels and Ti alloys [1, 2]. This method has some advantages such as [1, 2]:

1. Low cost
2. No protective shielding gas which may be toxic
3. No need of electrodes, because electric arc may be harmful for eyes
4. Not any crack formation and porosity, right after bonding because of the low input of total heat
5. Successful results in the welding of dissimilar materials

As shown in Figure 1, in FSW process, joining is done with the help of frictional heat generated at the faying surfaces of the two sheets to be joined with the specially designed rotating tool, which travels down the length of the contacting plates [1-3]. This produces a highly plastically deformed zone by the associated stirring action.

As the case may be with any new joining technique, for the successful application of FSSW as a viable joining technique, it is imperative to have a thorough understanding of the weld strength. The strength of friction stir spot welds is believed to depend primarily on two factors: weld process conditions and tool geometry. Weld process conditions include tool rotational speed, plunge depth and hold time. Tool geometry variations include shoulder geometry and pin geometry. It has been reported that the strength of friction stir spot welds mainly depends on the size of the weld region, which is further closely related to process conditions [3-6].

The previous research works are focused on the effect of process parameters, on the microstructure and tensile properties of friction stir welded joints. There are limited studies which model and predict the FSW process using various techniques such as artificial neural network. Cavaliere et al. [7], Zadpoor et al. [8] and Afrin et al. [9] ana-

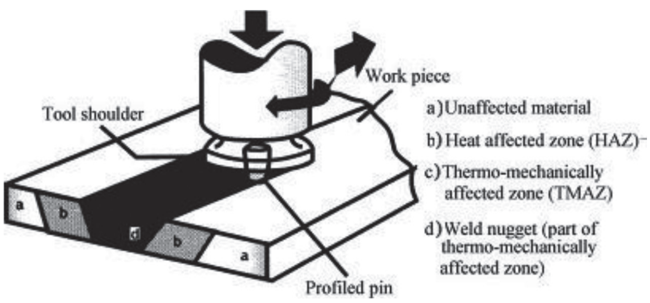

Figure 1: Schematic illustration of FSW process [3]

Chemical composition (wt.-%)	Fe	Si	Cu	Mn	Mg	Zn	Ti	Al
	0.40	0.25	0.05	0.05	0.05	0.07	0.04	99.50
Mechanical properties	Yield strength (MPa)		Tensile strength (MPa)		Elongation (%)		Hardness (HB)	
	68.67		104.96		3		35	

Table 1: Chemical and mechanical properties of EN AW 1050 aluminum alloy [13]

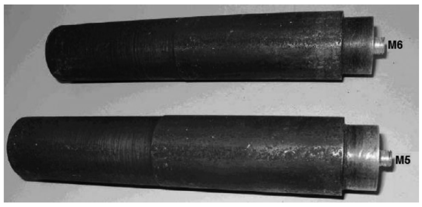

Figure 3: Tools used in the FSW process

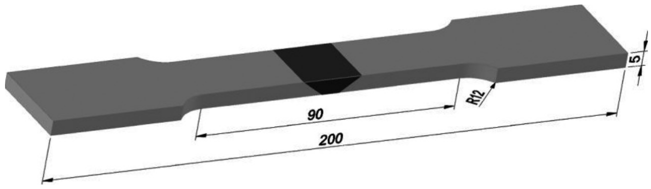

Figure 2: Shape and dimensions of the specimens

lyzed the effect of FSW process parameters on the mechanical and microstructural properties of dissimilar aluminum alloy joints. Zhou et al. [10] investigated the microstructures and fatigue properties of friction stir welded Al–Mg alloy. Ericsson and Sandstrom [11] reported that the value of the tool rotation (w) and traverse speed (v) are determined experimentally according to material to be welded. Gharacheh et al. [12] have determined that, increasing the ratio of rotational speed to traverse speed decreases the yield and ultimate strength of FSW joints.

The present study is focused on the modeling and prediction of the tensile shear strength and percent elongation of FSW welded EN AW 1050 aluminum alloy using Taguchi-based fuzzy logic method.

Experimental setup and procedure

Workpiece material. EN AW 1050 aluminum alloy material was used as a workpiece material with a thickness of 5 mm. The composition and mechanical properties of workpiece material are listed in Table 1.

The specimens were cut out in 100 mm width and 200 mm length. Then, the tensile test samples were taken from the welded specimens according to EN 10002-1. The configuration and dimension of the specimens used throughout the work is given in Figure 2.

FSW parameters. The main parameters of FSW are properties of material to be welded, tool material, tool geometry, tool rotation, welding speed and angle between axis of tool and vertical milling machine tool holder axis. In this study, weld travel speed (V, mm/min)), pin diameter (D, mm) and tool rotation (w, rpm) were selected as variable weld parameters (input parameters) while weld strength (TS, MPa) and percent elongation (E, %) were used as responses (output parameters) during the experiments. Three weld shear strength and elongation measurements were made and their average was taken as weld shear strength and elongation value. AISI 1050 steel was used as FSW tool material. The tool was manufactured with shoulder and pin diameters of 20 mm and M5 and M6, respectively, as shown in Figure 3. The tool was hardened to 52 HRC before the welding applications in order to prevent any deformation and wear. FSW welding was performed using a conventional vertical milling machine. Figure 4 shows the vertical milling machine used in FSW welding experiments.

Figure 4: Conventional vertical milling machine used in FSW process

During the experiments, the tool material, tool geometry and workpiece material were kept constant, whereas the other parameters (welding travel speed, pin diameter, and tool rotation) were altered according to the Taguchi experimental plan given below.

Experimental design and FSW process parameters

In full factorial design, the number of experimental runs exponentially increases as the number of factors as well as their level increases. This results in huge experimentation cost and considerable time [14, 15]. So, in order to compromise these two adverse factors and to search the optimal process condition by a limited number of experimental runs, Taguchi L_{16} orthogonal array consisting of 16 sets of data has been selected to plan the experiments of FSW process. Experiments have been conducted with the process parameters given in Table 2 to obtain the FSW on EN AW 1050 aluminum alloy. The feasible space for the FSW parameters was defined by varying the weld travel speed in the range of 40-112 mm/min, the pin diameter in the range of M5-M6 mm and the tool rotation in the range of 1400-2000 mm.

Table 3 shows the selected design matrix based on Taguchi L_{16} orthogonal array consisting of 16 sets of coded conditions and the experimental results for the responses of TS and E. All these data have been utilized for developing fuzzy logic algorithm and rules within the experimental domain.

Fuzzy logic

Fuzzy logic is a form of many-valued logic; it deals with reasoning that is fluid or approximate rather than fixed and exact. In contrast with “crisp logic”, where binary sets have two-valued logic: true or false, fuzzy logic variables may have a truth value that ranges between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false [16]. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions [16]. Fuzzy logic began with the proposal of fuzzy set theory by Lotfi Zadeh in 1965 [17, 18]. Fuzzy logic is concerned with the continuous transition from truth to falsity states [19, 20], as opposed to the discrete true and false transition in binary logic. The possibility theory of fuzzy logic provides a measure of the potential ability of a subset in belonging to another subset [21]. It is shown that probability theory is a special situation of possibility theory [19, 22]. Fuzzy logic has a wider concept and range of applications than many statistical methods [19]. Engineering applications of fuzzy logic uses the continuous transition in subset membership to transform a problem from crisp numeric to fuzzy linguistic domains. Instead of operating with numeric values of variables and using mathematical functions to describe relationships, fuzzy logic uses common everyday language to describe variables and uses fuzzy linguistic rules to define relationships [19].

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier as indicated in Figure 5. First, the fuzzifier uses membership functions to fuzzify the FSW parameters and the responses of tensile shear strength and percent elongation values of welded samples. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value [23]. Finally, the defuzzifier converts the fuzzy value into crisp numbers.

Results and discussions

In the following, the concept of fuzzy reasoning is described briefly based on the three-input one-output fuzzy logic unit. The fuzzy rule base consists of a group of if then control rules with the three inputs, x_1, x_2, x_3, and two outputs, y_1 and y_2, as given in Eq. (1) [23].

Rule 1: if x_1 is A_1 and x_2 is B_1 and x_3 is C_1 then y_1 is D_1 and y_2 is E_1 else
Rule 2: if x_1 is A_2 and x_2 is B_2 and x_3 is C_2 then y_1 is D_2 and y_2 is E_2 else
•
• (1)
•
Rule n: if x_1 is A_n and x_2 is B_n and x_3 is C_n then y_1 is D_n and y_2 is E_n else

A_i, B_i, C_i, D_i and E_i are fuzzy subsets defined by the corresponding membership functions such as $A\mu_i$, $B\mu_i$, $C\mu_i$, $D\mu_i$, and $E\mu_i$. The fuzzy inference engine which performs a fuzzy inference on fuzzy rules in order to generate a fuzzy value by taking max–min inference (Eq. (2)) to generate a fuzzy value [24].

$$\begin{aligned} \mu_{C_0}(Y) &= (\mu_{A_1}(X_1) \wedge \mu_{B_1}(X_2) \wedge \mu_{C_1}(X_3) \wedge \mu_{D_1}(Y)) \vee \ldots \\ \mu_{A_n}(X_1) &= (\mu_{B_n}(X_2) \wedge \mu_{C_n}(X_3) \wedge \mu_{D_n}(Y_1) \wedge \mu_{E_n}(Y_2)) \end{aligned} \tag{2}$$

Where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. In the present

FSW parameters	Notation	Unit	Levels of factors			
			1	2	3	4
Weld travel speed	V	mm·min^{-1}	40	56	80	112
Pin diameter	D	mm	M5	M6	-	-
Tool rotation	w	rpm	1400	2000	-	-

Table 2: Cutting parameters and their limits

Run No.	Coded parameter level			Experimental plan			Experimental results	
	V	D	w	V (mm·min^{-1})	D (mm)	W (rpm)	TS (MPa)	E (%)
1	1	1	1	40	M5	1400	89.07	15.75
2	1	1	1	40	M5	1400	88.87	15.97
3	1	2	2	40	M6	2000	89.66	15.40
4	1	2	2	40	M6	2000	91.33	14.80
5	2	1	1	56	M5	1400	92.21	13.06
6	2	1	1	56	M5	1400	91.72	16.06
7	2	2	2	56	M6	2000	90.54	12.50
8	2	2	2	56	M6	2000	91.33	17.8
9	3	1	2	80	M5	2000	91.23	15.00
10	3	1	2	80	M5	2000	89.66	15.25
11	3	2	1	80	M6	1400	88.97	14.05
12	3	2	1	80	M6	1400	89.27	15.21
13	4	1	2	112	M5	2000	93.09	17.25
14	4	1	2	112	M5	2000	92.99	17.12
15	4	2	1	112	M6	1400	92.80	16.74
16	4	2	1	112	M6	1400	92.21	15.65

Table 3: Orthogonal array L_{16} of the experimental runs and results

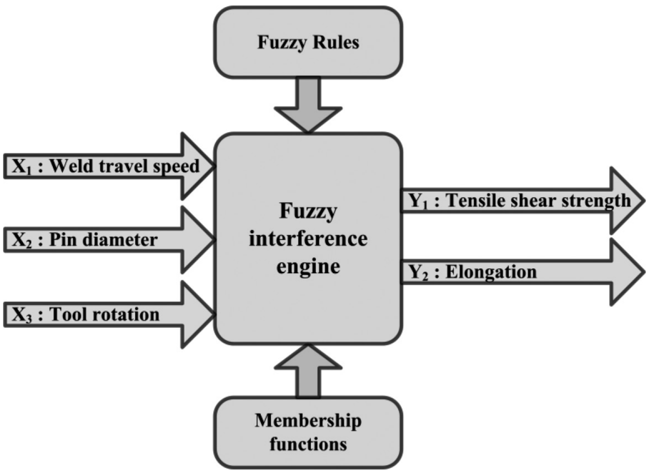

Figure 5: 3-input and 2-output fuzzy logic system

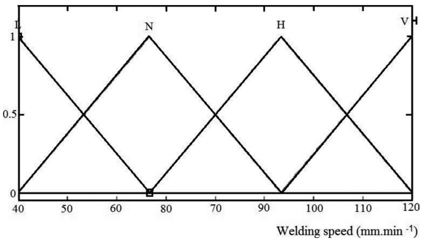

Figure 6: Membership function for welding speed (L: low, N: normal, H: high, VH: very high)

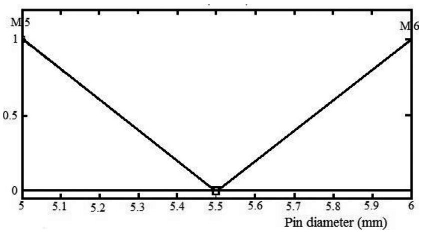

Figure 7: Membership function for pin diameter

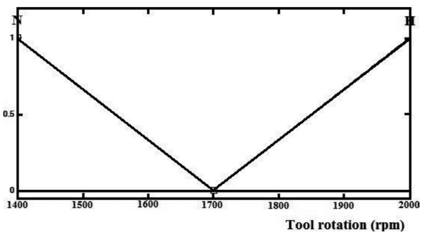

Figure 8: Membership function for tool rotation (N: normal, H: high)

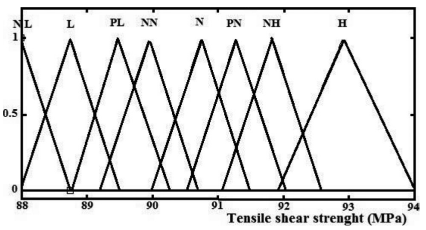

Figure 9: Membership function for tensile shear strength (NL: negative low, PL: positive low, NN: negative normal, N: normal, PN: positive normal, NH: negative high, H: high)

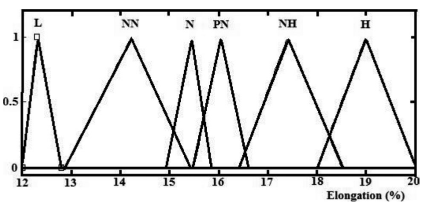

Figure 10: Membership function for elongation (L: low, NN: negative normal, N: normal, PN: positive normal, NH: negative high, H: high)

study, triangular membership function is used to convert the tensile shear strength values into fuzzy numbers. Figures 6 to 8 and Figures 9 to 10 show the membership functions for input and outputs parameters, respectively.

As a next step, the defuzzifier converts the fuzzy value into a crisp number. Centroid defuzzification method (center of gravity) was used in order to convert the fuzzified inputs and outputs. The centroid defuzzification method is given in Eq. (3).

The fuzzy logic rule viewer is shown graphically in Figure 11. Sixteen rows represent sixteen fuzzy rules and the first three columns represent inputs. The last two columns column gives the defuzzified TS and E values. The fuzzy prediction model is obtained by using MATLAB v7.10.0 (R2010a) fuzzy logic tool box.

Finally, the complete defuzzified values of TS and E were compared with the experimental values as depicted in Table 4.

Based on the results given in Table 4, the absolute average error between the experimental and predicted values for TS and E was calculated as 0.45 and 3.97 %, respectively.

The fit of the fuzzy predicted models were measured by the correlation coefficient of R^2. High R^2 values of 0.931 for TS and 0.895 for E were obtained as shown in Figures 12 and 13. Also, an acceptable agreement with the adjusted determination coefficient is necessary. In the present study, the Adj-R^2 values of 0.98 and 0.88 were obtained for TS and E. The values of R^2 and Adj-R^2 are close to 1.0, which indicates high correlation between the experi-

Run No.	Experimental results		Fuzzy prediction	
	TS (MPa)	E (%)	TS (MPa)	E (%)
1	89.07	15.75	88.80	15.40
2	88.87	15.97	88.75	15.42
3	89.66	15.40	89.13	15.40
4	91.33	14.80	90.64	14.33
5	92.21	13.06	91.27	15.40
6	91.72	16.06	90.52	13.78
7	90.54	12.50	90.61	16.06
8	91.33	17.8	90.91	15.21
9	91.23	15.00	88.75	14.17
10	89.66	15.25	89.19	14.52
11	88.97	14.05	91.52	16.83
12	89.27	15.21	92.95	16.78
13	93.09	17.25	91.83	15.40
14	92.99	17.12	91.51	15.81
15	92.80	16.74	91.27	16.05
16	92.21	15.65	90.91	18.30
			Average error: 0.45 %	Average error: 3.97 %

Table 4: Comparison of experimental and fuzzy predicted results

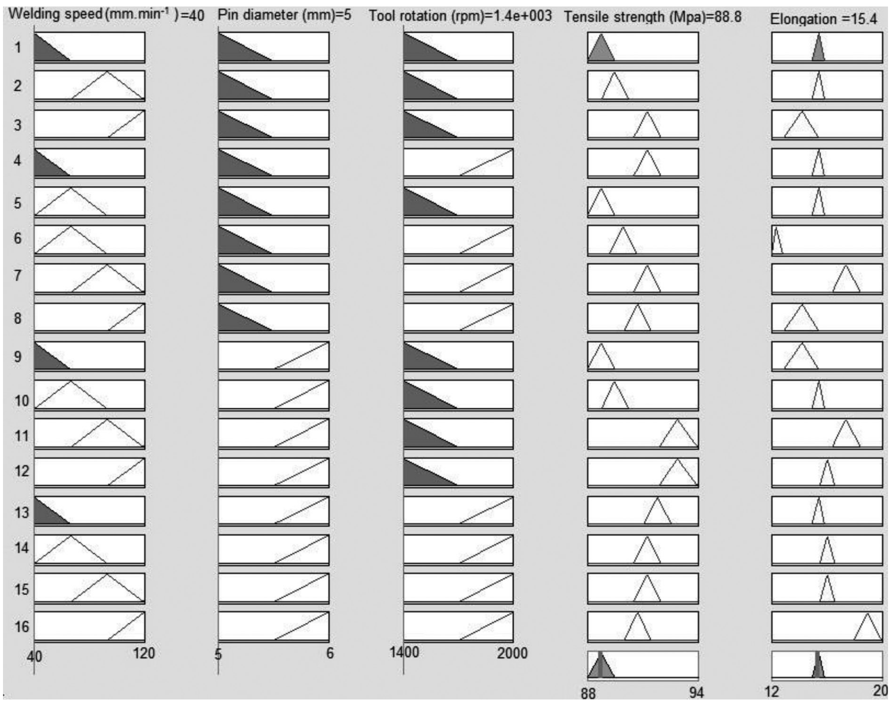

Figure 11: Fuzzy model and rule viewer for prediction of TS and E in FSW process

mental values and the fuzzy predicted values. This indicates that the fuzzy model provides a close relationship between the input and the output variables.

Conclusions

This study has been concentrated on the complete fuzzy model for modeling and prediction of tensile shear strength and elongation in friction stir welding process for EN AW 1050 aluminum alloy. Fuzzy rules and triangular membership functions which gave the minimum prediction error has been constructed in order to increase the correlation coefficient. Predictive fuzzy model shows the close agreement with the experimental results as obtained the correlation coefficients of 0.931 and 0.895 for tensile shear strength and percent elongation, respectively.

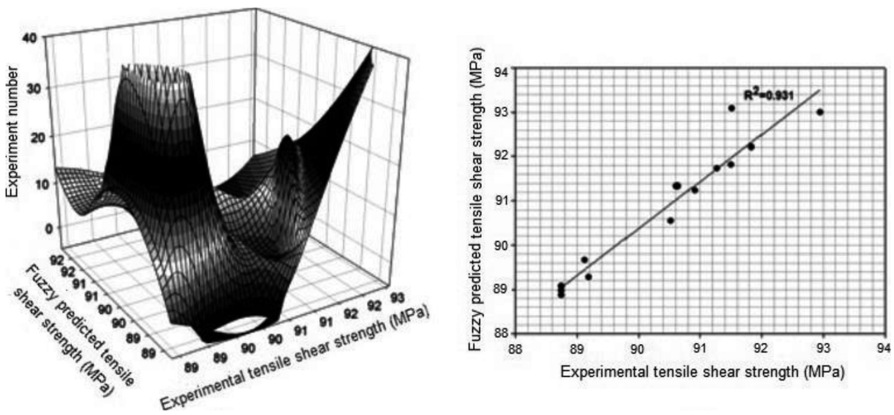

Figure 12: a) 3D surface views of the tensile shear strength results, b) comparison of fuzzy predicted vs. experimental tensile shear strength

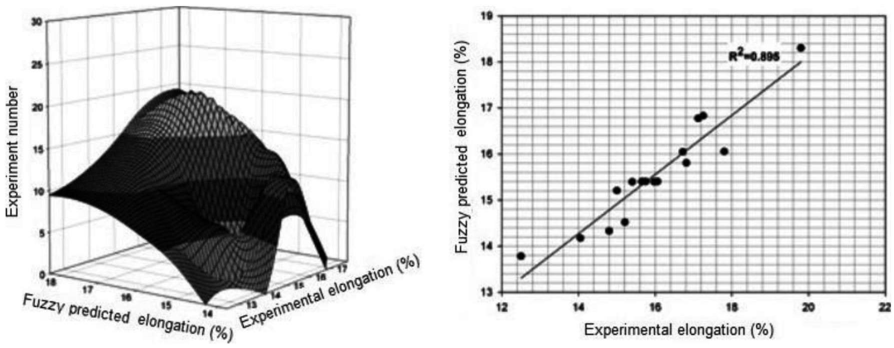

Figure 13: a) 3D surface views of the elongation, b) comparison of fuzzy predicted vs. experimental elongation

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Abstract

Zugscherfestigkeit und Verlängerung von rührreibgeschweißten Teilen vorhergesagt mittels Taguchi-basierter Fuzzy-Logik. In dem vorliegenden Beitrag wird ein Modell basierend auf Fuzzy-Logik vorgestellt, mit dem die Scherzugfestigkeit und die prozentuale Verlängerung von Teilen modelliert und vorhergesagt werden kann, die mit dem Rührreibschweißprozess (Friction Stir Welding (FSW)) hergestellt wurden. Hierzu wurde ein L_{16} orthogonales Taguchi-Array verwendet, um die Parameter und ihre Werte zu planen und auszuwählen. Die Schweißgeschwindigkeit, der Pin-Durchmesser und die Werkzeugrotation wurden als Inputvariablen ausgewählt. Daher wurde ein Fuzzy-Modell mit drei Input-Parametern und drei Output-Parametern und ihren entsprechenden Werten verwendet, um diese Variablen mit den Antworten der Scherzugfestigkeit und der prozentualen Verlängerungen zu korrelieren, wobei die Fuzzy-Regeln verwendet wurden, die basierend auf experimentellen Ergebnissen ermittelt wurden. Es ergab sich eine enge Übereinstimmung der mit Fuzzy-Logik vorhergesagten mit den experimentellen Ergebnissen mit den Korrelationskoeffizienten von 0.931 für die Scherzugfestigkeit bzw. 0.895 für die Verlängerung.

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