

Fuzzy Logic Model for Combined Monitoring of Weld Strength and Nugget Hardness of Friction Stir Weld

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Abstract

In this paper, the development of a fuzzy logic model to monitor the weld tensile strength and nugget hardness of Friction Stir Welding (FSW) is reported. AA6063-T6 aluminum alloy plates, of 6 mm thickness, were joined, using the FSW process. FSW is a complex solid-state process, and the process parameters, spindle rotational speed, traverse feed rate, and tool shoulder plunge depth, are significant in deciding the mechanical properties of FSW joints. For these 3 significant process parameters and their 3 levels, the most suitable array, Taguchi's L₂₇ orthogonal array, was selected for the experiments. Based on the experimental results, a Mamdani type fuzzy model was developed to forecast the combined FSW weld tensile strength and nugget hardness. The developed fuzzy model was experimentally validated. As compared with the experimental results, the fuzzy model results exhibit errors of 2.13 and 1.31 % for weld tensile strength and nugget hardness, respectively. The proposed approach could be employed for the online monitoring and control of the FSW process within the range of the process parameters.

Keywords: Friction stir welding, fuzzy logic, aluminum alloys, tensile strength, hardness

Introduction

Friction Stir Welding (FSW) is a solid-state metal joining process, invented at The Welding Institute (TWI) in 1991, in which a non-consumable rotating shoulder-pin type tool is plunged slowly into the butting faces of the work pieces and navigated along the joint line [1]. The relative motion between the tool pin and the work plate generates frictional heat that develops a plasticized region around the tool and forms a solid-phase joint. FSW demonstrates good weldments in the joining of aluminum, steel, titanium, and dissimilar alloys. This technique has been applied for welding aluminum alloys in the aerospace, automotive, and ship building industries [2]. FSW provides enhanced joint properties and performance, low deformation after welding, a major reduction in production costs, and a lessened need for skilled labor over conventional joining techniques [3].

It is important to investigate the mechanical properties of a welded joint in order to describe its performance, and tensile strength and hardness are the most vital mechanical properties. Rajakumar *et al.* [4] established the relationships between FSW parameters and tensile strength, hardness, and the corrosion rate of FSW AA6061-T6 aluminum alloy joints, and optimized the FSW parameters in order to obtain maximum strength using reference surface methodology.

For complex processes like FSW, which involves multi-input and multi-output parameters, a wide spectrum of on-line controllers have been developed by the manufacturing industry [5]. The fuzzy theory is a well-known theory, and is an ideal tool for multi-input multi-output processes due to its tolerance of

indefinite data and ability to model non-linear arbitrary functions. It can also be blended with conventional control techniques [6]. It is highly appropriate for defining the relationship between process inputs and desired outputs. Tarn and Cheng [7] demonstrated a fuzzy control of the feed rate in end milling. Variations in the cutting parameters and nonlinearities in the processes are the drawbacks in the development of proper mathematical models. Fuzzy logic technology provides an alternative solution and models a process as a black box with input and output variables [8,9].

The electromagnetic radiation fundamental frequencies emitted during the tensile failure of the FSW welds, produced at different process parameters, were analyzed using fuzzy modeling [10]. The fundamental frequency of weld failures were estimated from the fuzzy model and found to be closer to the experimental results. Berkan and Trubatch [11] found that the number of the membership functions (MF) and their locations on the universe of discourse influence the fuzzy algorithm, compared to the shape variations of MFs. Zhang *et al.* [12] has developed a systematic data-driven fuzzy modeling approach to model FSW behavior relating to AA5083 aluminum alloy with microstructural features, mechanical properties, and overall weld quality. The extracted models proved to be accurate, interpretable, and robust, and can be applied to facilitate the optimal design of process parameters to achieve the desired welding properties.

Hence, the FSW process parameters, spindle speed, feed rate, and plunge depth, influence the mechanical properties FSW joints. There is a gap between predicting these properties for various parameters and for different materials. This gap could be filled by developing a fuzzy logic based model for the FSW process. In this work, an attempt was made to develop a straightforward fuzzy model for the prediction of weld strength, along with nugget hardness, within the range of the process parameters, which could provide a good joint through using FSW.

Experimental

FSW experiments were carried out in a conventional milling machine with a vertical attachment, a rigid clamping fixture, and an automatic feed control system. The milling machine spindle had a speed range of 45 to 2000 rpm, a maximum permissible load of 250 N, and a spindle motor power of 5 HP. Single pass welding procedure was used to fabricate the butt joints. In this investigation, AA6063-6 aluminum alloy plates of size $100 \times 50 \times 6$ mm³ were used as a work material, which is extensively used in architectural and furniture fabrication. The experiments were carried out with square pin profile tools. The tools were fabricated from stainless steel SS316 round bars. As per the available literature [13], the pin diameter was made one third of the shoulder's diameter to ensure good quality welds.

The arrangement of the FSW experimental setup is depicted in **Figure 1(a)**. In the experimental setup tool, shoulder diameter was fixed at 18 mm; this is 3 times the thickness of the work plates (thickness 6 mm). The **Figure 1(b)** shows a schematic diagram and photographs of the tool used in this study. As suggested by Chao *et al.* [14], the pin length of the welding tool was kept a little shorter than the work plate thickness, to avoid contact with the backing plate surface and to bring fragments into the weld. The tool had a pin length of 5.5 mm, and the square pin diagonal length was equal to 6 mm.

Experimental process parameters

Design of experiments (DOE) is a systematic approach to determine the relationship between the factors affecting the process and its corresponding outcome. Taguchi method is a standardized approach in DOE to determine the best combination of inputs to plan the experiments. In the present work, experiments were conducted based on the Taguchi's L₂₇ orthogonal array with three levels of process parameters as shown in **Table 1**.

Table 1 FSW Process parameters and levels.

Notation	Process parameters	Unit	Levels		
			1	2	3
TR	Tool Rotational Speed	rpm	710	1000	1400
TF	Traverse Feed Rate	mm/min	20	40	80
PD	Shoulder Plunge Depth	mm	0.2	0.3	0.4

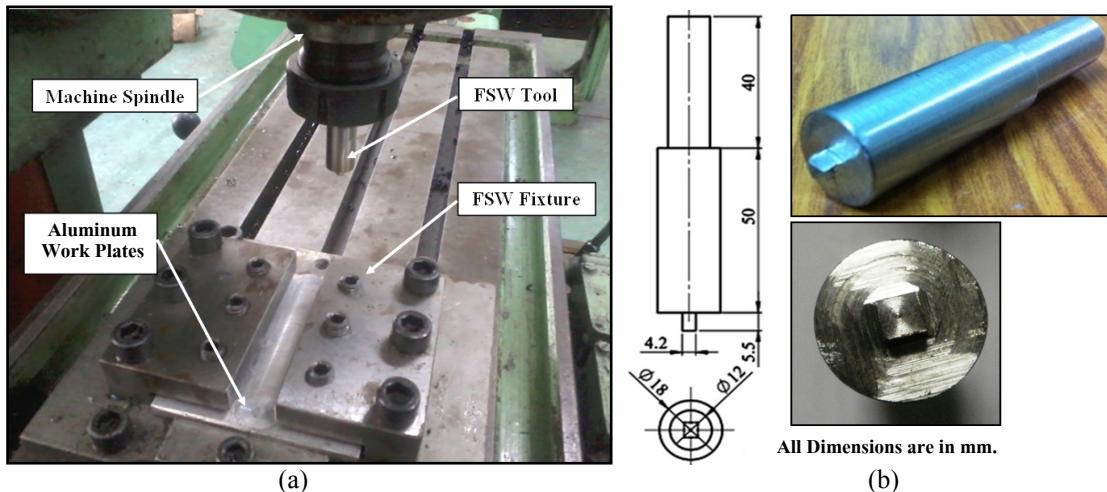


Figure 1 (a) FSW experimental setup and (b) FSW tool.

Mechanical properties of welded joints

Specimens produced through FSW were visually inspected for exterior weld defects. A sample of such a plate is shown in **Figure 2**. For the tensile test, standard welded specimens were prepared using the wire cut Electrical Discharge Machining (EDM) process.

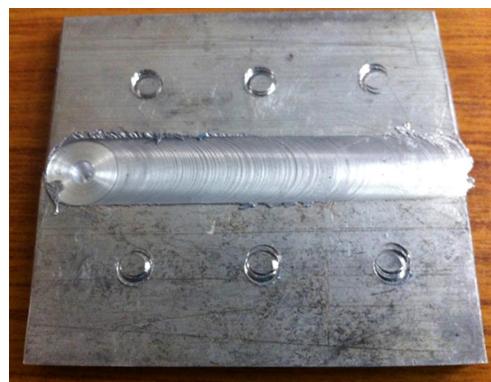


Figure 2 FSW specimen.

The tensile test specimens were prepared according to the ASTM standard E8, as shown in **Figures 3(a)** and **3(b)**. The tensile strength of the FSW specimen was evaluated using a computerized electronic tensometer, and the tensile curve for the specimen is shown in **Figure 3(c)**.

The micro hardness at the mid of the weld nugget was tested using Vickers hardness testing machine for all specimens, and the result for a sample specimen is given in **Figure 4**. The obtained experimental results of the weld tensile strength and nugget hardness of the weld specimen for different process parameter levels are depicted in **Table 2**.

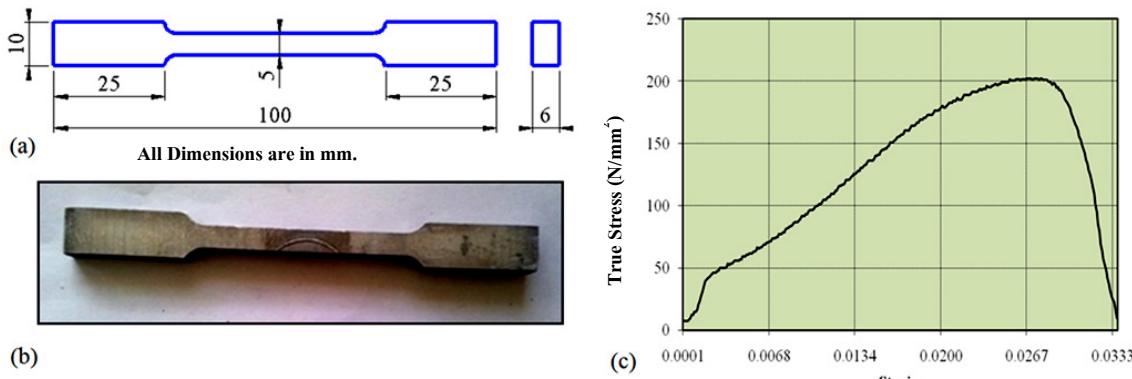


Figure 3 (a) Dimensions of tensile test specimen, (b) Photograph of tensile test specimen and (c) Tensile curve for specimen produced at 1000 rpm and 40 mm/min.

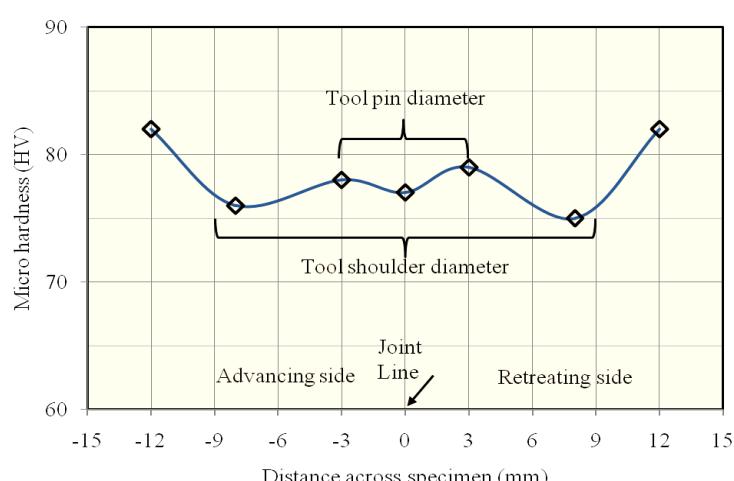


Figure 4 Micro hardness curve across the FSW AA6063T6 aluminum alloy specimen produced with tool rotational speed of 1000 rpm and feed rate 40 mm/min.

It is observed from **Table 2** that a good response occurs when the input parameters are at a tool speed of 1000 rpm, a feed rate of 40 mm/min, and a plunge depth of 0.3 mm. At optimum conditions, the energy input to the process leads to increased work-tool interface temperatures. The generated heat in the weld zone helps to create a better stir of softened work material and increase fine material compression given by plunge depth and tool tilt angle. However, it is identified that the spindle speed, feed rate, and plunge depth should be restricted to optimum values to obtain good weld tensile strength and nugget hardness.

Table 2 Experimental matrix (L_{27}) and output responses (weld tensile strength and nugget hardness).

Expt. No.	Input parameters and levels			Output parameters	
	TR (rpm)	TF (mm/min)	PD (mm)	Weld tensile strength (MPa)	Nugget hardness (HV)
1	710	20	0.2	188	71
2	710	20	0.3	174	68
3	710	20	0.4	167	66
4	710	40	0.2	193	72
5	710	40	0.3	196	73
6	710	40	0.4	175	66
7	710	80	0.2	188	71
8	710	80	0.3	191	73
9	710	80	0.4	186	70
10	1000	20	0.2	192	72
11	1000	20	0.3	192	72
12	1000	20	0.4	180	68
13	1000	40	0.2	191	72
14	1000	40	0.3	201	77
15	1000	40	0.4	195	75
16	1000	80	0.2	194	72
17	1000	80	0.3	196	73
18	1000	80	0.4	187	72
19	1400	20	0.2	182	69
20	1400	20	0.3	187	71
21	1400	20	0.4	176	67
22	1400	40	0.2	186	70
23	1400	40	0.3	197	75
24	1400	40	0.4	175	67
25	1400	80	0.2	178	68
26	1400	80	0.3	180	68
27	1400	80	0.4	175	65

Table 3 Fuzzy linguistic variables and range of process parameters.

Inputs				Range
Notation	Process parameters	Unit	Linguistic variables	
TR	Tool Rotation	rpm	L- Low	710 - 1400
TF	Traverse feed rate	mm/min	M- Medium	20 - 80
PD	Shoulder Plunge Depth	mm	H- High	0.2 - 0.4
Responses				
TS	Weld tensile strength	MPa	L- Low	167 - 201
NH	Nugget Hardness	Hv	M- Medium H- High	65 - 77

Development of fuzzy logic model based on FSW process parameters

In the present work, a fuzzy logic model, based on the Mamdani method, was developed for assessing the weld tensile strength and nugget hardness of FSW components as the output parameters, and tool rotational speed, feed rate, and plunge depth as the input parameters. The fuzzy linguistic variables and characteristics for input and output parameters are shown in **Table 3**. Each input variable had 3 membership functions, which were Low, Medium, and High. The output variables also had 3 membership functions, Low, Medium, and High. MATLAB 8.0 software was used to develop and simulate the fuzzy model.

Membership functions

The choices of membership functions (MF) for fuzzification were dependent on the relevant event. The shape of the MF was a depiction of uncertainty in the fuzzy variable. Experiments were conducted for 3 levels of process parameters based on DOE to obtain good weldment. In this model, each input and output parameter has 3 levels and corresponding membership functions. The Gaussian membership function was used to describe the fuzzy sets for input variables, in order to enhance them and address the complex interactions of input parameters. Triangular membership function generally possesses gradually increasing and decreasing characteristics with one distinct value. Therefore, the output variables are inferred by triangular membership functions. Fuzzy membership functions for the input are shown in **Figures 5(a) - 5(c)** and the corresponding output variables are shown in **Figures 5(d) and 5(e)**. The parameters for the Gaussian and triangular membership functions were altered by post-tuning the fuzzy model viewer for higher prediction accuracy using MATLAB software.

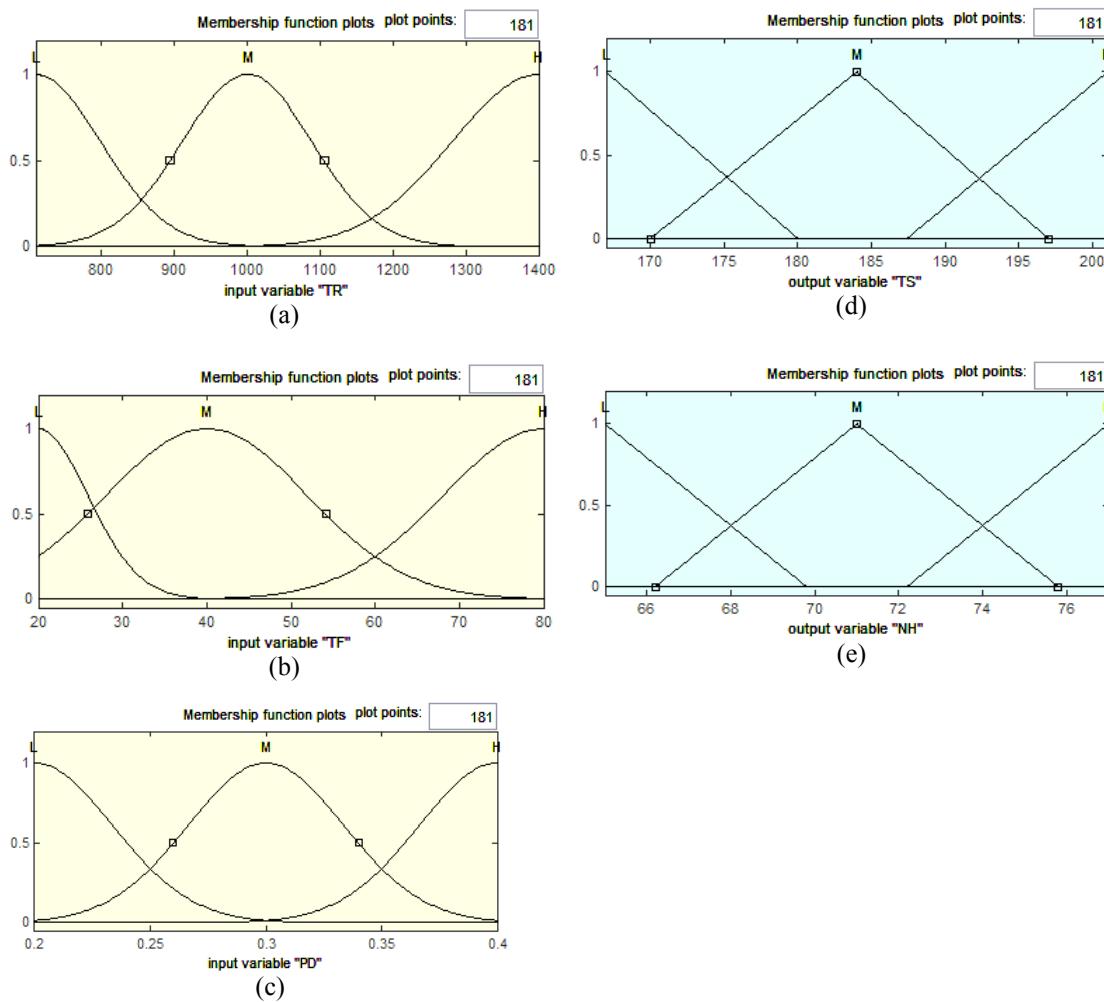


Figure 5 Membership functions of input and output process parameters; (a) Rotational speed of the tool, (b) Feed rate of the tool, (c) Plunge depth of the tool, (d) Weld tensile strength of the weld joint and (e) Hardness of the weld joint.

Fuzzy rules

A fuzzy inference engine performs inference operations on activated fuzzy rules at each computational cycle to constitute an aggregate output [15]. The fuzzy rules are formed with fuzzy inputs, which could be obtained from experts, experiments, and past data of the process [16]. Experimental data were used to develop the rules for a Mamdani type fuzzy inference system with 3 inputs and 2 outputs. A rule base with a set of 27 rules was formulated, based on the input process parameters for predicting the weld tensile strength and hardness of weld joints as the output, as shown in **Figure 6**. The ranges of process parameters were narrow in this FSW process. Hence, all input parameter combinations were used to obtain consistent outputs.

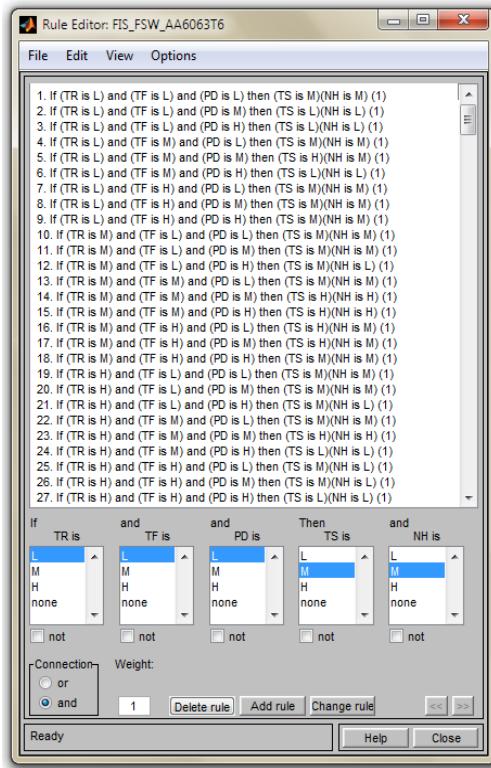


Figure 6 Fuzzy rules set.

Defuzzification

In this fuzzy logic model, a centroid of area (COA) defuzzification scheme is engaged, due to its extensive acceptance and capability in giving accurate results, rather than other defuzzification methods. The overall fuzzy output of the Mamdani fuzzy model results from adopting the AND logic operation into the triggered rules, and the rule viewer is shown in **Figure 7**.

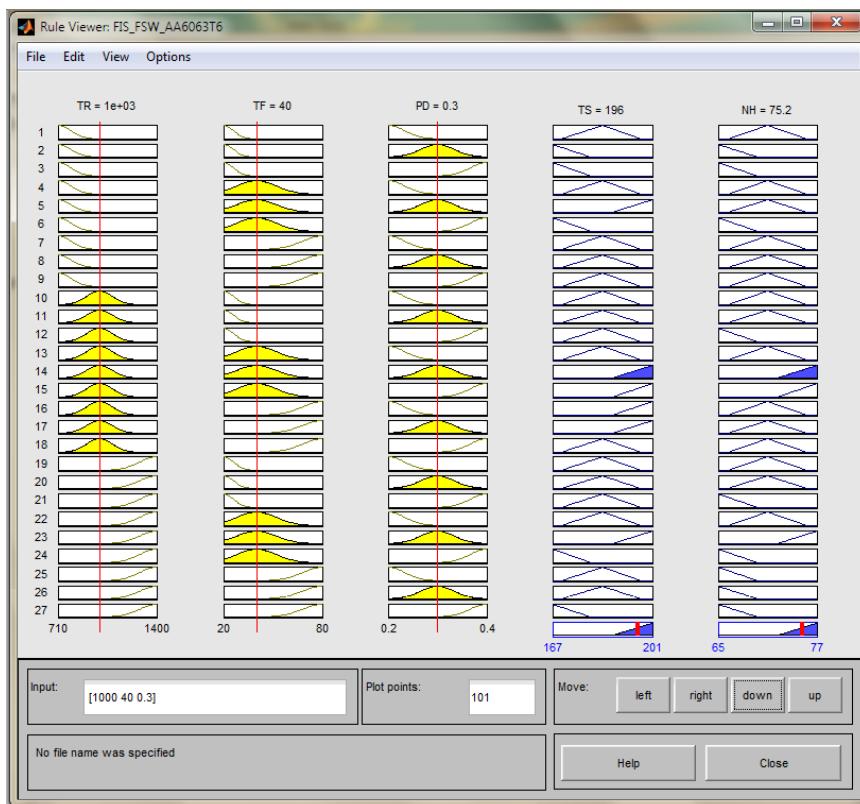


Figure 7 Fuzzy rule viewer.

Results and discussions

The weld tensile strength and nugget hardness of FSW aluminum components were simulated from the developed fuzzy model. The experimental data set was used to investigate fuzzy model accuracy and error. The individual error percentage was calculated using the Eq. (1);

$$\text{Individual Error (\%)} = \frac{\text{Experimental data} - \text{Fuzzy predicted data}}{\text{Experimental data}} \times 100 \quad (1)$$

Figures 8(a) and 8(b) shows the comparison between the fuzzy model estimated values of output parameters with that of the experimental results. The absolute error percentage between the experimental and fuzzy logic model predicted values of output parameters were computed by averaging the individual error percentage. The fuzzy logic model estimated results demonstrated a close agreement with the experimental data, with an absolute error of 2.14 % for weld tensile strength and 1.39 % for weld nugget hardness, respectively. Hence, the developed fuzzy logic model could be used to predict the joint tensile strength and weld nugget hardness within the specified range of input parameters considered.

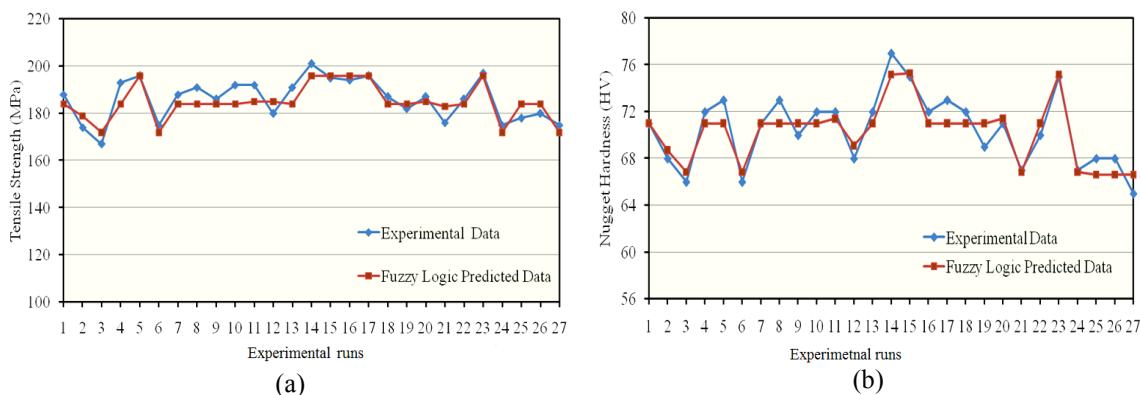


Figure 8 Comparison of fuzzy model estimated FSW (a) joint tensile strength with experimental results and (b) nugget hardness with experimental results.

Surface plots for effect of process parameters

The fuzzy model was simulated for different values of input process parameters and the weld tensile strength of FSW joint was predicted, as shown in **Figures 9(a) - 9(c)**. As can be seen in **Figure 9(a)**, there is significant increase in the tensile strength of the FSW joint with increases in tool rotational speed and tool feed rate. However, the weld tensile strength reached a most favorable value in the speed range of 900 to 1100 rpm and with a 40 to 50 mm/min feed rate. It is clearly seen that both the tool rotational speed and the feed rate are very significant in changing the weld tensile strength. The higher values of input parameters provide the lower tensile strength of the FSW joint.

It is observed from **Figure 9(b)** that there is an increase in the tensile strength of the FSW joint with increases in tool rotational speed and tool plunge depth. However, the tensile strength reached a favorable value in the speed range of 900 to 1100 rpm and at a 0.3 to 0.35 mm plunge depth. It is clearly seen that high rotational speed and plunge depth provides lower tensile strength of the FSW joint. As can be seen in **Figure 9(c)**, there is significant increase in the tensile strength of the FSW joint with increases in tool feed rate and plunge depth. The lower values of plunge depth and feed rate provide the lower tensile strength of the FSW joint. A plunge depth of 0.3 mm and a feed rate above 40 mm/min provides a considerable value of tensile strength.

Figures 9(d) - 9(f) are surface graphs showing the relationship between input parameters and the fuzzy logic model predicted nugget hardness of the FSW joint. The tool rotational speed, feed rate, and plunge depth influence the change in nugget hardness. As can be observed from **Figure 9(a)**, there is a significant increase in the nugget hardness of the FSW joint with an increase in tool feed rate. However, it reaches a most favorable value in the speed range of 1000 to 1200 rpm and with a 40 to 55 mm/min feed rate. The higher values of tool rotational speed and feed rate provide the lower nugget hardness of the FSW joint.

Figure 9(b) shows that there is an increase in the nugget hardness of the FSW joint with an increase in tool rotational speed and in tool plunge depth. However, the nugget hardness reaches a favorable value in the range of tool rotational speed between 1000 and 1100 rpm and at a plunge depth between 0.3 and 0.35 mm. It is observed from **Figure 9(c)** that there is a considerable value of the nugget hardness of the FSW joint with a plunge depth above 0.27 mm, and a tool feed rate between 40 and 50 mm/min. It is obvious that the intense plunge depth provides lower nugget hardness in the FSW joint.

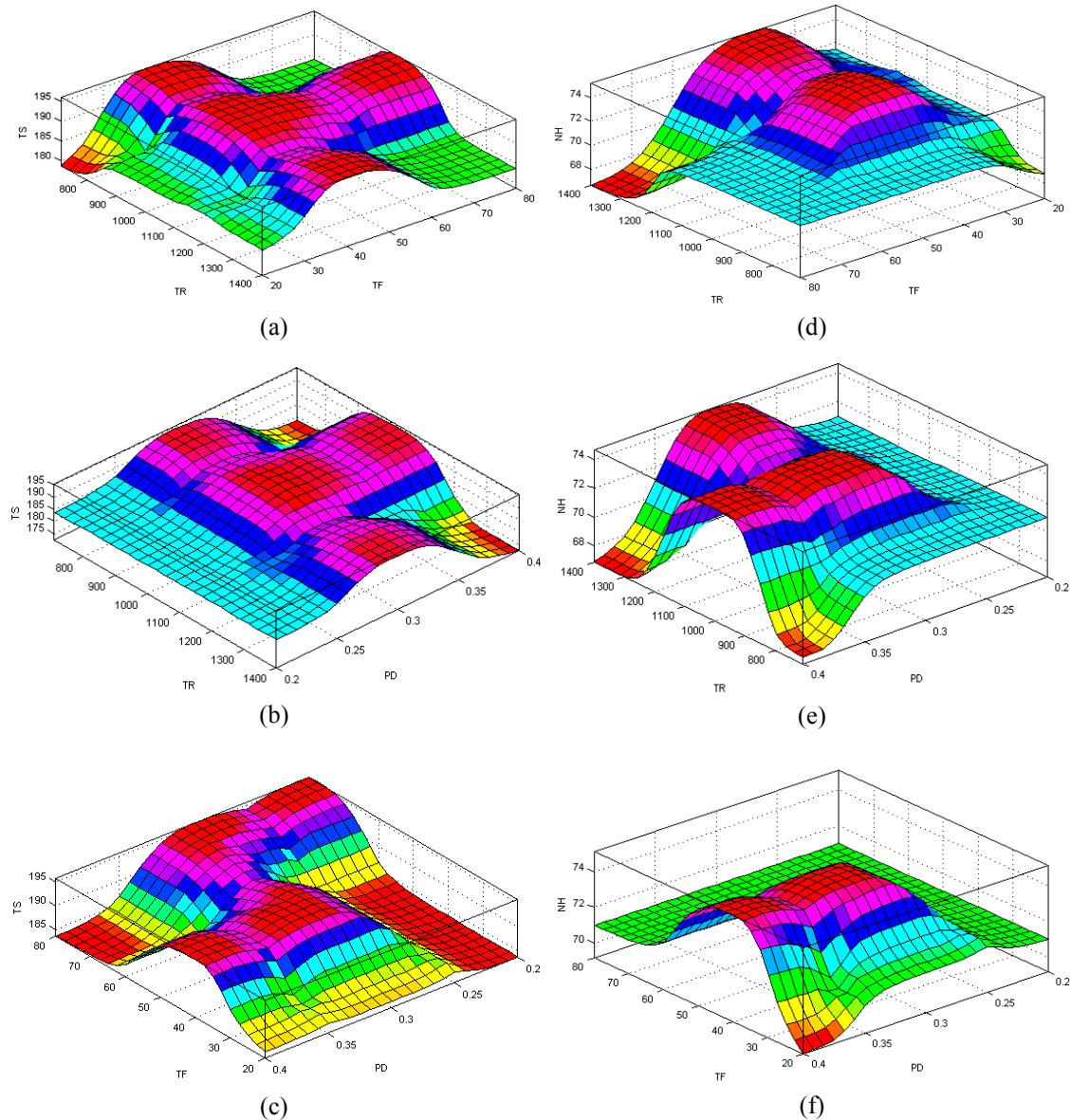


Figure 9 Fuzzy logic predicted mechanical properties for input process parameters; (a) Weld tensile strength for rotational speed and feed rate, (b) Weld tensile strength relative for rotational speed and plunge depth, (c) Weld tensile strength for tool feed rate and plunge depth, (d) Nugget hardness for rotational speed and tool feed rate, (e) Nugget hardness for tool rotational speed and plunge depth and (f) Nugget hardness for feed rate and tool plunge depth.

Conclusions

The experimental work reveals sensitive process parameters which are used to generate membership functions and fuzzy rules for a fuzzy inference system. It was found that the input process parameters of tool rotational speed, traverse feed rate, and shoulder plunge depth notably influence both the weld tensile strength and nugget hardness of FSW joints. The developed fuzzy logic model performs well in monitoring the weld tensile strength and nugget hardness of friction stir butt-welded AA6063-T6 aluminum alloy flat plates of 6 mm thickness. Additionally, the simulation showed that the favorable output parameters occur in a range of input process parameters, and the simulation results proved that the fuzzy inference scheme has good compliance with the process conditions within a range of process parameters. The experimental and simulation analysis confirmed a good agreement between the fuzzy model and the experimental results, with the accuracy of 97.86 and 98.61 % for the weld tensile strength and nugget hardness of FSW joints, respectively. The presented fuzzy logic scheme could be used as a control algorithm for the online monitoring and control of FSW processes within a significant range of process parameters, in order to obtain good weldment.

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