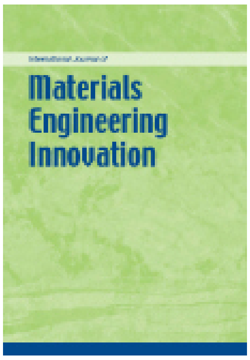

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Using fuzzy logic to predict the influence of the tool shoulder geometry of friction stir welded Al 6082 T6 alloy

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Abstract: Friction stir welding (FSW) and its variants are important welding processes in many industries, including aerospace, railway, robotics and computers. Since welding plays a vital role in enhancing production and productivity, the effect of tool shoulder geometry on weld quality must be investigated. The weld quality is affected by tool geometry, welding speed, tool traverse speed, tool inclination angle, and so on. Consequently, the interaction of such parameters influences the weld quality, which becomes difficult to predict. In this research, welding was performed on Al 6082 T6 alloy using two separate shoulder geometries (raised and recessed shoulder) at three different welding rates and tool transverse speeds. Further, the ultimate tensile strength (UTS) and the microhardness of the material were used in weld quality evaluation. Two adaptive network-based fuzzy inference systems (ANFIS) were used to train and evaluate the UTS and microhardness, respectively. The Takagi-Sugeno fuzzy inference system was used to find the effect of tool shoulder geometry on the weld quality.

Keywords: adaptive network-based fuzzy inference systems; ANFIS; artificial intelligence; artificial neural network; ANN; friction stir welding; FSW; genetic algorithm; Al 6082 T6 alloy.

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1 Overview

In a global economic civilisation, the need for electricity is increasing every day (Threadgill et al., 2009). Integrating low-weight, super-strength metals such as aluminium, magnesium, and titanium in cars utilised in aero, overland, and marine transportation is one of the most successful methods to achieve this goal (Salloomi et al., 2020; Dorbane et al., 2016; Câmara et al., 2012). These metals are particularly difficult to join using standard welding techniques. To get the most out of this lightweight, high-strength alloy, they will need special treatment (Mironov et al., 2018; Nagaraj et al., 2020). The difficulty of generating high-strength, fatigue, and fracture-resistant welds for commercial uses has long restricted structural welding (Mishra and Ma, 2005; Murr, 2015). Furthermore, there is a significant drop in mechanical properties when compared to the basic material. Traditional welding procedures are inappropriate for joining these metals because of these characteristics. To overcome these roadblocks, industries have focused on innovative manufacturing processes.

Friction stir welding (FSW) has gained popularity in recent years, enabling businesses to employ it in a wide range of industries and on a wide range of metal alloys (Nagaraj et al., 2020; Cho, 2008; Günen et al., 2018). This approach, which allowed the effective mixing of several metal sets, was used to combine low melting point metals that are difficult to join using traditional welding procedures. FSW was created in 1991 by The Welding Institute (TWI) of the UK as a solid-state joining procedure for aluminium alloys (Mishra and Ma, 2005; Murr, 2015). Between the contacting perimeters of the sheets or plates to be coupled and pushed via the union line, a non-consumable rotating tool with a specifically shaped pin and shoulder are positioned. Tool material, base metal material, thickness, tool speed in revolutions per minute (RPM), pin design, pin length, tool travel speed, heat input, and tool head angle are all factors that influence the weld quality in the FSW process. Each of these aspects is separate, yet they all interact (Cipriani et al., 2004). The most suitable processing factors should be selected while keeping the conflicting circumstances of this factor in mind to generate items with the best mechanical qualities while keeping costs low (D'Souza et al., 2020; Yoon et al., 2016; Kim et al., 2014). Because of recent breakthroughs in artificial intelligence (AI) systems, the usage of AI techniques in a variety of engineering fields has exploded (Ankarali et al., 2004; Yavuz, 2004). Because of their high accuracy, simplicity of application, and adaptability to any field, AI is rapidly being used in many areas. In the FSW cycle, AI processes are used to optimise and analyse a variety of factors to achieve top quality at an optimal cost. Different factors include tool metal, base metal, base metal thickness, welding speed in RPM, welding feed, pin shape, pin length, heat input information and tool head angle (Dinaharan and Murugan, 2012; Mondal et al., 2017; Karimnejad et al., 2021). Artificial neural networks (ANNs), fuzzy logic meta-heuristic algorithms, wavelet, machine learning, hybrid systems, adaptive network-based fuzzy inference system (ANFIS), heuristic-ANN, genetic algorithm (GA), and heuristic-fuzzy are the most common AI approaches which may be employed in predicting the weld quality.

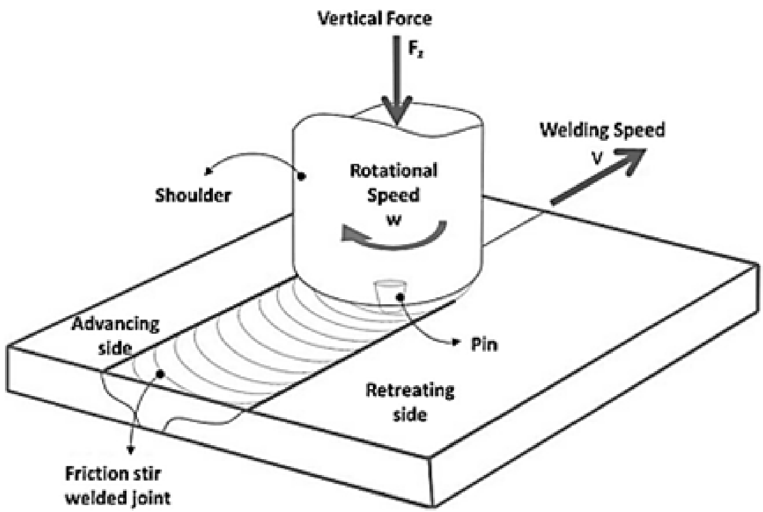
The main objective of this research is to predict the FSW weld quality of Al 6082 T6 alloy. The welding is carried out in different combinations of distinct FSW tools and shoulder shapes. In addition, the welding is carried out using a variety of process conditions. During this study, two different AI systems were used.

2 Friction welding technology

FSW is a method of joining metals without the need for fillers or fusion materials. Furthermore, when welding, the temperature does not surpass the base metals' melting point. As a consequence, it is known as a solid-state welding procedure. This welding method is most often used on non-ferrous alloys with low melting points. Even though aluminium is the most commonly used material, however, titanium, magnesium, copper, steel, polyethylene, and polycarbonate are also often utilised. Because there is no heat production before melting, there is no structural modification in the welded zone or the base metal following welding. FSW may be used to join metals that are not compatible.

The underlying principle of FSW is deceptively simple. A non-consumable rotating tool with a specifically designed pin and shoulder is positioned between the contacting perimeter of the plate material to be connected and moved along the joint line (refer to Figure 1). The tool's primary function is to warm the base metal and to provide material mobility for the forming of the union. Heat is created at the connecting side of the material due to friction between the tool and the top surface of the base metal, and the base metal deformed plastically. Localised heating softens the material around the pin, and unique combinations of tool rotation, tool translation, and shoulder geometry cause material displacement from the front to the back of the pin. During the first stage of welding, the revolving pin is touched to the union line with a length that does not exceed the thickness of the base metal. Heat is created when the spinning pin contacts the plates, and the material begins to soften.

Figure 1 Principal of FSW



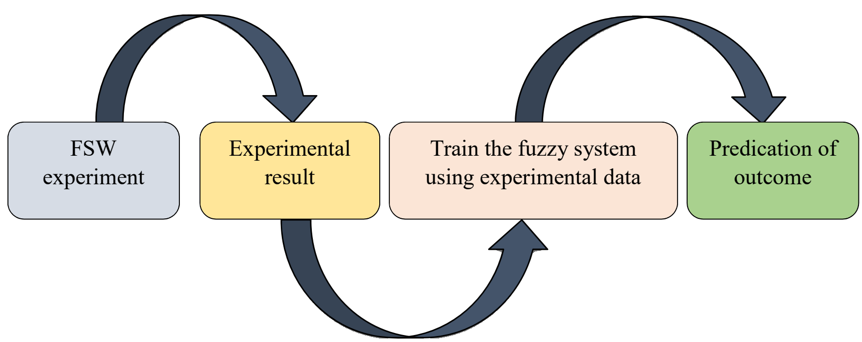
Source: Eren et al. (2021)

During welding, the oxide that has formed along the combination line is destroyed. With advancing movement, the heat-sensitive materials are combined and merged, and the remaining joined component cools to form the solid state (Mishra and Ma, 2005; Murr, 2015). FSW is an environmentally friendly and sustainable welding process that consumes less energy than traditional welding procedures and can fuse a variety of materials.

Several researchers have worked in the FSW domain. Ouyang et al. (2006) investigated the temperature distribution and microstructure of a weld made with Al (6061-T6) and 99.8% copper using this method. Intermetallic complexes including CuAl2, CuAl, and Cu9Al4 were discovered in the joint field. Dey et al. (2009) studied the FSW procedure for stainless steel and titanium. They concluded that composite carbides, which are made up of reinforced particles, may be used as a tool material. They identified the chemicals as tungsten and cobalt carbides. The Al (6061-T6) alloy is often used in FSW (Rajakumar et al., 2010). This alloy, they believe, creates a lightweight joint with strong mechanical properties, such as high strength and corrosion resistance. They discovered that the strength of the nugget zone and the grain size affected the joint strength. To estimate the tensile strength and grain size of the joining material, they constructed an empirical connection between input and output parameters for the FSW of Al (6061-T6). The FSW characteristics of AA6061 aluminium alloy and Al-Mg_2Si composite materials were tested (Sharghi and Farzadi, 2018). The goal is to use a computational fluid dynamic (CFD) model to investigate the strain rate, nugget form, and viscoelastic material movement in the FSW process (Sharghi and Farzadi, 2018). Aali (2020) used a novel titanium alloy, Ti4Al2V, and experimented with spindle rotation to see how it influenced the quality of the weld. He noticed that the toughness of the weld increased as the rotating speed increased. He also observed that to minimise flaws like pitting, exact synchronisation between the tool's rotary and transversal speeds is essential (Aali, 2020). Zhou et al. (2019) employed FSW to compare the tool wear, internal structure, and mechanical properties of AA6061 and Ti6Al4V alloys after welding. Aside from that, there are a variety of FSW uses and research on different Al alloys.

FSW's idea and approach may be used for a variety of metals and non-metals, resulting in substantial progress and development in the industrial sectors. The most crucial and difficult job for new material is determining the most influential production factor. AI has emerged as one of the most effective methods for finding the influential factor. Figure 2 depicts the use of FSW technology in conjunction with the fuzzy interface.

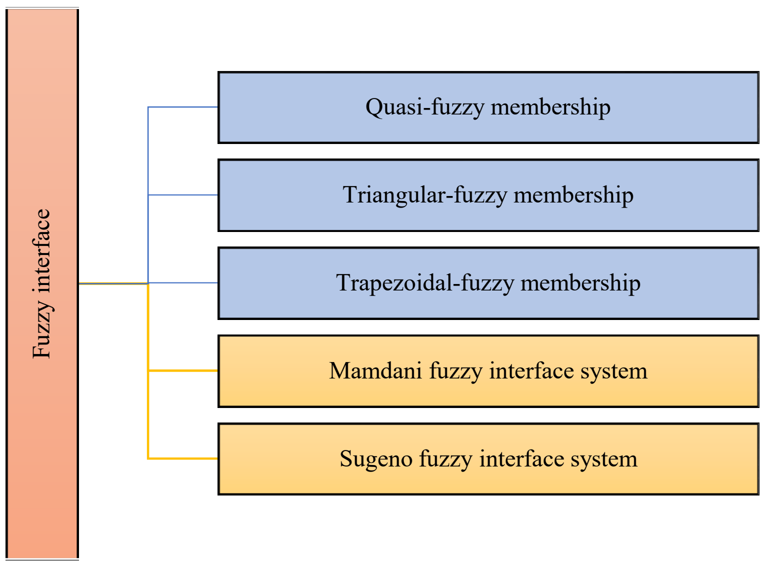
Figure 2 Flowchart of integration of FSW technology and fuzzy interface (see online version for colours)



3 Adaptive network-based fuzzy inference system

An ANFIS is a sort of ANN based on the Takagi-Sugeno fuzzy inference system. Because it combines neural networks with fuzzy logic concepts, it can make use of both in a single framework (Barath et al., 2018). Its inference system consists of a set of fuzzy if-then rules that may be approximated to nonlinear functions using artificial learning. As a consequence, ANFIS has earned the reputation of being a universal estimator. The GA-based best parameters may be utilised to apply the ANFIS more efficiently and optimally (Paschen et al., 2020). A fuzzy algorithm provides an ability to learn and adapt a system based on earlier data, as well as make judgments. The interaction of fuzzy-based systems with intelligence, adaptability, and intentionality in its proposed algorithms is continually expanding fuzzy value (Allam and Dhunny, 2019). Fuzzy systems have been utilised for a variety of optimisation, classification, analysis, and prediction applications in almost all interdisciplinary disciplines. Fuzzy technologies are commonly employed with experimental design approaches such as Taguchi optimisation method, response surface methodology (RSM), and others to enhance the reliability of optimal solution prediction.

Figure 3 Different types of fuzzy interface (see online version for colours)



Source: Alam et al. (2022)

AI helps in a variety of manufacturing processes to gain productivity and efficiency by automating processes and procedures that would normally need the involvement of humans. Additionally, AI can grasp enormous volumes of data, something that no human being is capable of Eren et al. (2021). As a direct result of these benefits, the number of businesses that make use of fuzzy interface techniques to solve problems in the industrial sector is continually growing. Figure 3 illustrates some of the many different fuzzy interface techniques. Fuzzy inference is a method that interprets the values in the input vector and, based on some sets of rules, assigns values to the output vector. In fuzzy logic, the truth of any statement becomes a matter of a degree. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made or patterns discerned (Alam et al., 2022). The process of fuzzy inference involves all of the pieces described so far, i.e., membership functions, fuzzy logic operators, and if-then rules. Two main types of fuzzy inference systems Mamdani-type and Sugeno-type can be implemented. These two types of inference systems vary somewhat in the way outputs are determined. Optimising FSW variables was accomplished by Dewan et al. (2016) abusage of an ANN model in combinations with a model of an ANFIS, which was developed specifically for this project. The researchers found that the ANFIS model performed much better than the ANN model (Dewan et al., 2016). Using ANN, simulation is carried out in MATLAB (Katherasan et al., 2014), they employed the PSO technique to optimise a set of L25 Taguchi orthogonal array of flux-cored arc welding operation variables. As a direct consequence of this, a wide array of AI algorithms is now available (Tansel et al., 2010; Kannan et al., 2014, 2017). In contrast to it, ANN and GA have been used in this investigation. ANNs are particularly effective when used for linear and nonlinear systems, as well as circumstances in which the system knowledge is imprecise.

4 Material and methodology

It is difficult to fuse Al 6082 T6 alloy using traditional welding techniques since it is built on the elements magnesium, silicon and manganese. Its chemical composition and mechanical properties are shown in Table 1. It contains magnesium, and aluminium alloy hence becoming exceedingly malleable while maintaining its strength. Because of these characteristics, it has swiftly replaced older aluminium alloys of the 6XXX family. Further, the plate was cut into pieces of 300 × 150 × 4 millimetres, thus a total length of 300 millimetres was obtained.

Table 1 Chemical composition and mechanical properties of Al 6082 T6 alloy

Material	Al	Si	Mg	Mn	Fe	Cr	Zn	Cu + Ag
% composition	Bal.	0.90	1.1	0.70	0.50	0.25	0.20	0.10

Mechanical properties

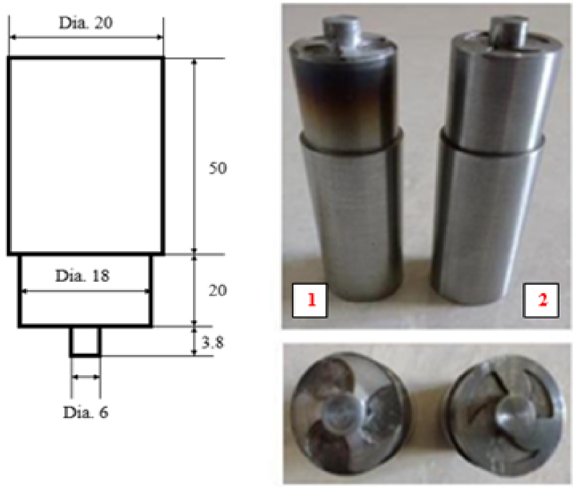
Property	Tensile strength	Yield strength	Elongation	Hardness
Value	280 MPa	240 MPa	10 %	95 HV

Source: Sameer and Birru (2019)

Since the FSW tool was made of H13, the tool wear was considerably low. Figure 4 depicts two distinct FSW tools, each of which has a circular pin profile with different shoulder geometry. During the process of developing the FSW tool, the ratio of the tool shoulder diameter to the pin diameter was maintained at 3 (Rajakumar et al., 2011; Rao and Naik, 2018; Elangovan and Balasubramanian, 2008; Malarvizhi and Balasubramanian, 2012). This has further prevented the FSW tool from coming into direct contact with the workpiece. The length of the FSW tool's pin is designed to be 2 millimetres shorter than the workpiece plate thickness (Mishra and Ma, 2005; Murr, 2015; Aali, 2020).

In the present research, the Taguchi technique of design of experiments was used as a statistical tool to optimise and plan the experiments. The FSW process variables and their respective levels are obtained and listed in Table 2. The experiment was designed using a mixed-level Taguchi design since the tool rotation speed, welding speed, and shoulder design each have three levels whereas the design of the experiment only has two levels. The mixed-level Taguchi approach is executed using the Minitab 18 software, which produces a total of 36 experiment variations for both tool-raised and recessed geometries according to the L36 orthogonal array. On the computer numerically controlled milling machine, a total of 36 different welding tests were carried out in the order specified by the experimental design (HASS, USA). The setup for the FSW process is shown in Figure 5.

Figure 4 Tool dimension and tool design (tool design 1 and tool design 2) (see online version for colours)



Note: All the dimensions are in mm.

Table 2 Levels of FSW process parameters

Parameter	*Tool design level*		
	1		*2*
	Raised		Recessed
	1	*2*	*3*
Tool rotation speed in RPM	2,300	2,500	2,700
Welding speed in mm/min	20	30	40

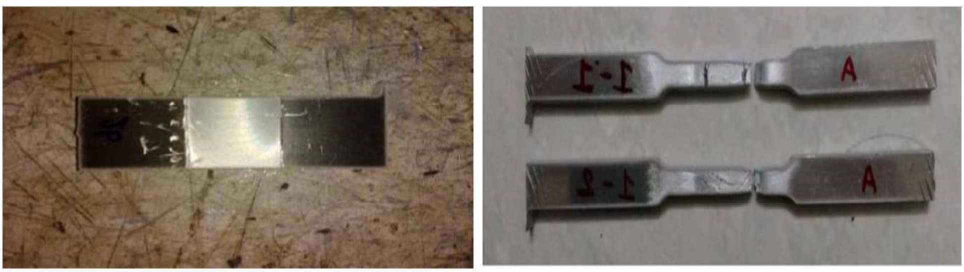
Figure 5 FSW welding setup (see online version for colours)

Table 3 Experimental result

Sr. no.	*Shoulder design*	*Tool rotation speed (RPM)*	*Tool travel speed (mm/min)*	*Average UTS (N/mm^2)*	*Microhardness (HV0.1)*
1	1	2,300	20	168	57
2	1	2,500	30	168	56
3	1	2,700	40	172	61
4	1	2,300	20	168	54
5	1	2,500	30	171	55
6	1	2,700	40	168	60
7	1	2,300	20	159	56
8	1	2,500	30	171	57
9	1	2,700	40	176	58
10	1	2,300	20	159	57
11	1	2,500	30	165	59
12	1	2,700	40	171	61
13	1	2,300	30	168	47
14	1	2,500	40	164	49
15	1	2,700	20	159	44
16	1	2,300	30	165	45
17	1	2,500	40	171	50
18	1	2,700	20	159	48
19	2	2,300	30	162	57
20	2	2,500	40	164	61
21	2	2,700	20	115	51
22	2	2,300	30	159	58
23	2	2,500	40	151	59
24	2	2,700	20	116	50
25	2	2,300	40	135	49
26	2	2,500	20	147	50
27	2	2,700	30	145	42
28	2	2,300	40	138	50
29	2	2,500	20	144	51
30	2	2,700	30	146	41
31	2	2,300	40	137	49
32	2	2,500	20	144	48
33	2	2,700	30	147	41
34	2	2,300	40	133	50
35	2	2,500	20	142	47
36	2	2,700	30	144	40

Table 3 presents the different combinations of input parameters that are obtained through the Taguchi L36 orthogonal array. In this experiment, the elements that were taken into consideration were the rotation speed, the travel speed, and the shoulder design of the FSW tool. After the welding, three tensile and one microhardness specimens are extracted, as shown in Figure 6 from each experimental weld run and the average of those three ultimate tensile strengths (UTSs) and microhardness are measured and listed in Table 3. The microhardness of the weld nugget portion as shown in Figure 6, was measured at three different positions near the centre of the nugget, which is lateral to the weld joint.

Figure 6 Test specimens (see online version for colours)



5 Results and discussion

On a plate of Al 6082 T6 alloy with a thickness of 4 millimetres, FSW experiments were carried out. Experiments are performed using two different FSW tools, each having a circular pin pro-file that has either a raised or recessed shoulder shape. During the whole welding process, there was no variation in the setting of the tool. The surface appearance of one of the welded samples is shown in Figure 7. The spindle rotation speed was 2,700 rpm, and the feed rate was 40 mm/min. The raised shoulder feature tool was used to create the sample. Table 3 provides a summary of the UTS and microhardness of each sample, which were evaluated by a UTM machine and a Vickers hardness tester machine, respectively, for each of the 36 weld tests. The UTS and microhardness values are presented in the same format.

Figure 7 Surface appearance (see online version for colours)

Figure 8 Fuzzy interface for (a) UTS and (b) microhardness

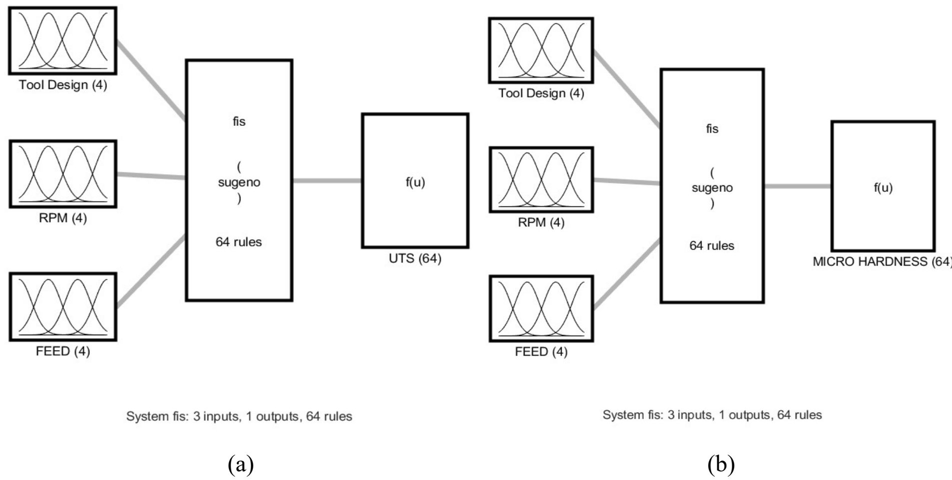


Figure 9 Membership functions for (a) tool design, (b) RPM and (c) feed (see online version for colours)

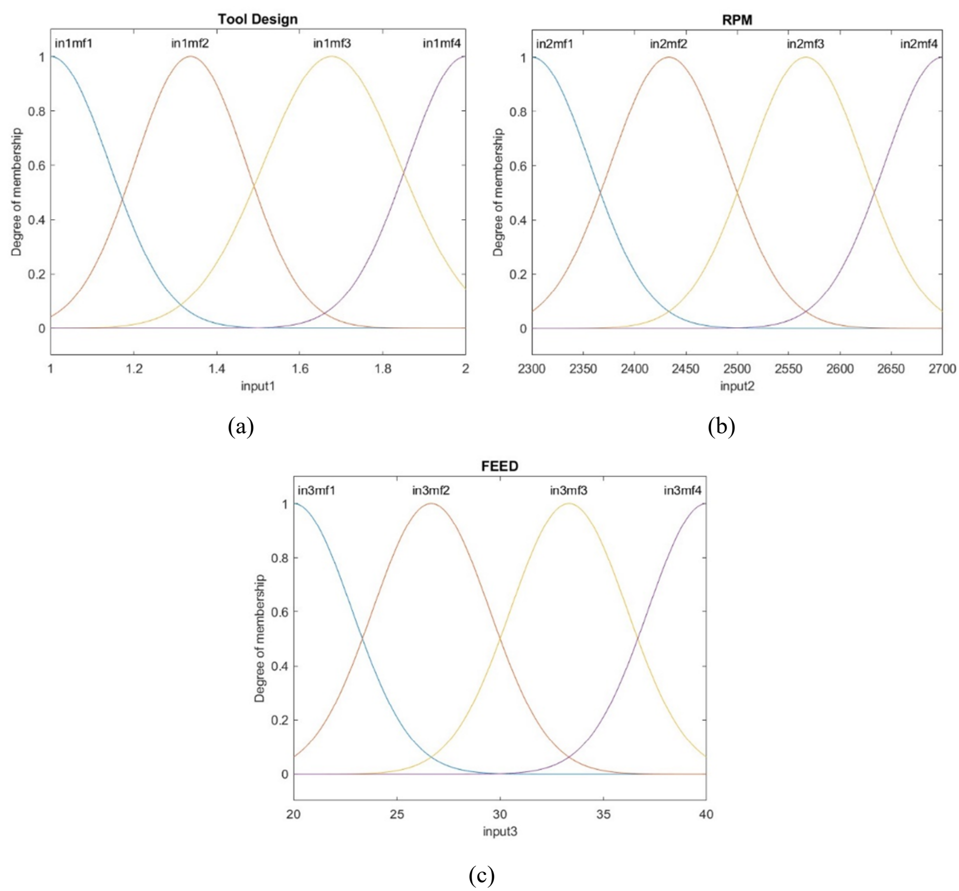
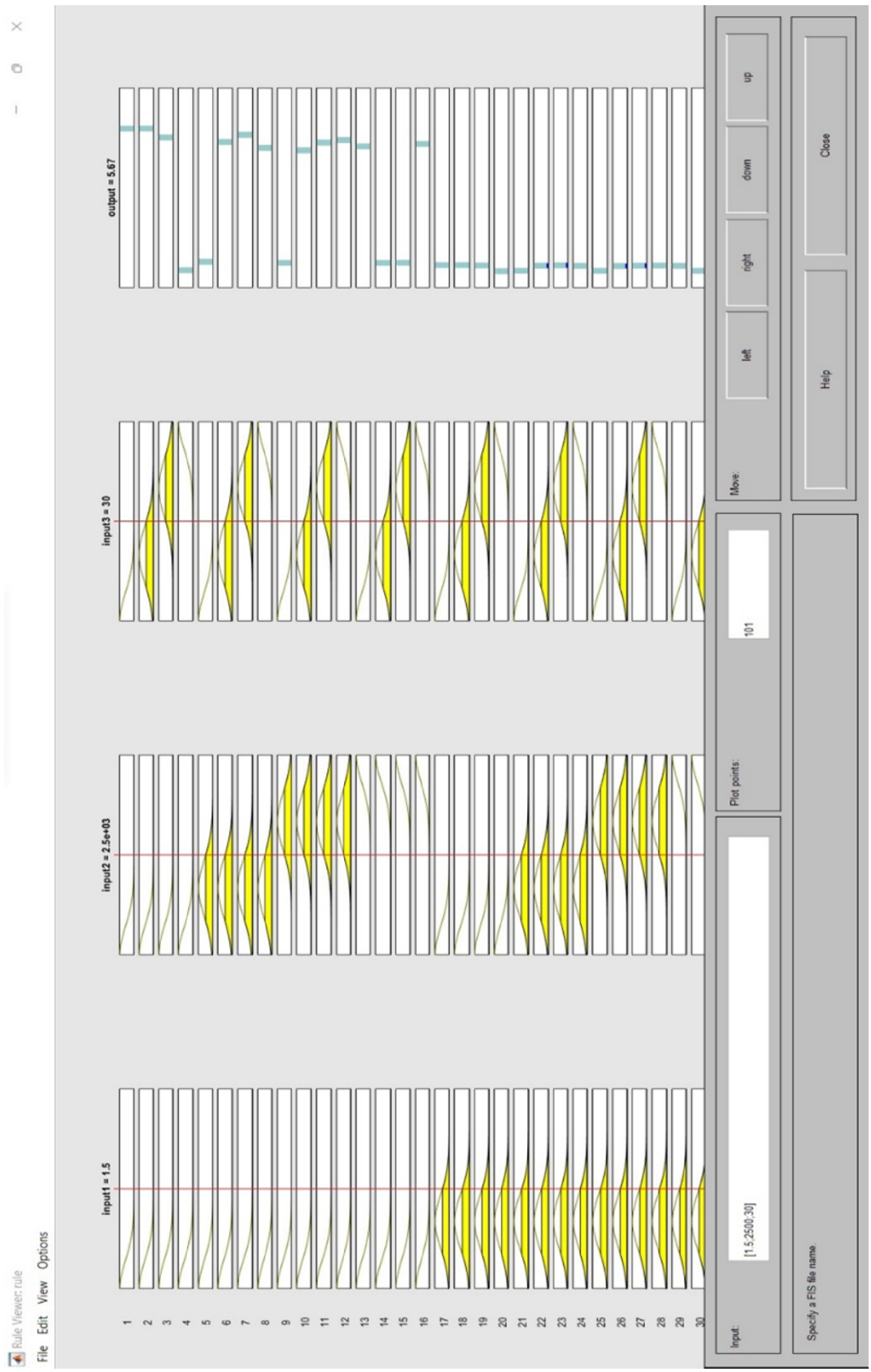


Figure 10 Fuzzy interface for rules (see online version for colours)



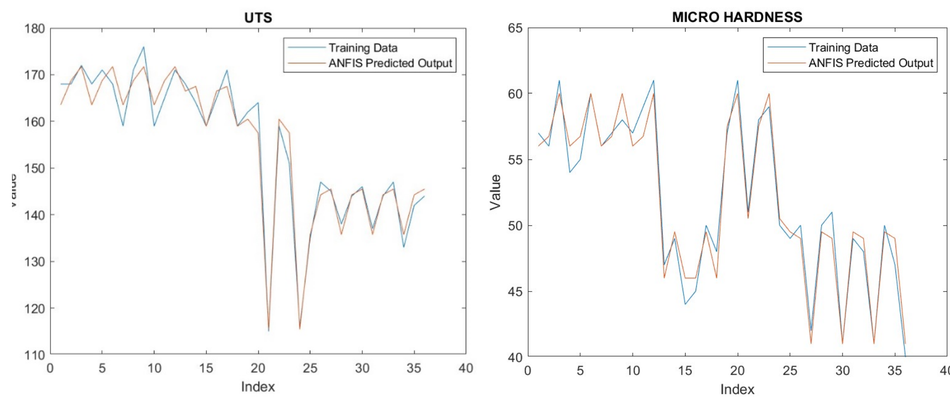
As shown in Figure 8, first training of data is carried out considering the three inputs of tool design, RPM, feed, and predicted UTS value subsequently followed by data training to predict microhardness (Shivakoti et al., 2019).

As shown in Figure 9, membership functions for three inputs arguments of tool design, RPM and feed were considered. The tool design has two designs (Threadgill et al., 2009; Salloomi et al., 2020) whereas the range of RPM is between [2,300–2,700] and feed is between [20–40].

As shown in Figure 10, three input variables of tool design, RPM, and feed were used to form the 64 rules. Each combination of tool design number, RPM, and feed was used to form rules for UTS and microhardness.

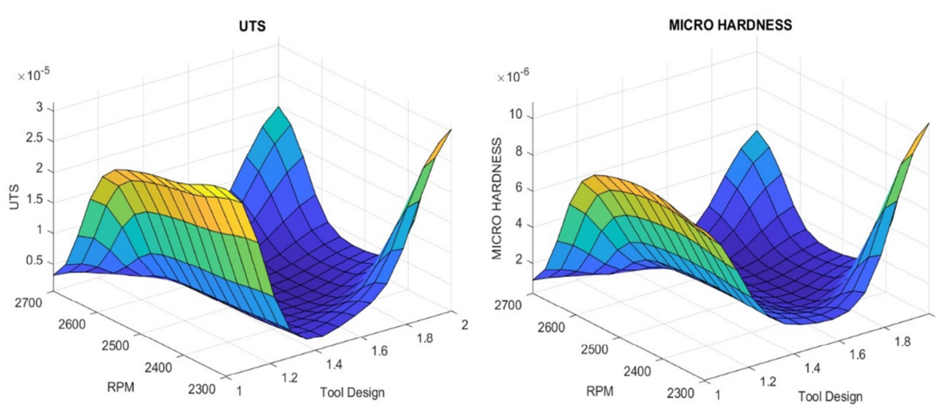
As shown in Figure 11, two fuzzy models were prepared to predict the UTS and microhardness and compared with actual values. The root mean square error (RMSE) was observed as 2.83 for UTS and 1.15 for microhardness.

Figure 11 Actual vs. predicted for (a) UTS and (b) microhardness (see online version for colours)



(a) (b)

Figure 12 Surface plot of (a) tool design number, RPM, feed with UTS and (b) tool design number, RPM, feed with microhardness (see online version for colours)



(a) (b)

Figure 12 shows the surface plots of tool design number, RPM, and feed to represent UTS and tool design number, RPM, and feed to represent microhardness. Thus, the relationship between two inputs was utilised for the output of UTS and microhardness. As per the surface plot of tool design number, RPM, feed with UTS and microhardness, it is seen that at higher RPM and feed, higher UTS and microhardness also increase.

6 Conclusions

For the purpose of this investigation, a total of 36 FSW tests were carried out using a pre-defined set of information parameters. The results of these experiments were analysed for the tensile strength and hardness of FSW welds on Al 6082 T6 alloy combinations. The following are some inevitable inferences that might be drawn from this: The results of the experiment demonstrate that there is a correlation between the welding speed, feed and UTS. The surface plot derived through ANFIS architecture shows that at higher RPM and feed, higher UTS with a good microhardness of the weld zone may be obtained.

At a tool rotation speed of 2,700 rpm and a welding speed of 40 mm/min, the greatest tensile strength of 176 N/mm^2 was attained. This was made possible by the use of higher tool shoulder geometry. The fuzzy model makes an autonomous prediction of the UTS and microhardness values based on the three inputs tool number, RPM, and feed. RMSE for the UTS and the microhardness are, respectively, 2.83 and 1.15.

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