IOP Conf. Series: Materials Science and Engineering **103** (2015) 012034 doi:10.1088/1757-899X/103/1/012034

Artificial neural networks application for modeling of friction stir welding effects on mechanical properties of 7075-T6 aluminum alloy

E Maleki[1]

Mechanical Engineering Department, Sharif University of Technology-International Campus, Kish Island, Iran

E-mail: maleki_erfan@kish.sharif.edu/ maleky.erfan@gmail.com

Abstract. Friction stir welding (FSW) is a relatively new solid-state joining technique that is widely adopted in manufacturing and industry fields to join different metallic alloys that are hard to weld by conventional fusion welding. Friction stir welding is a very complex process comprising several highly coupled physical phenomena. The complex geometry of some kinds of joints makes it difficult to develop an overall governing equations system for theoretical behavior analyse of the friction stir welded joints. Weld quality is predominantly affected by welding effective parameters, and the experiments are often time consuming and costly. On the other hand, employing artificial intelligence (AI) systems such as artificial neural networks (ANNs) as an efficient approach to solve the science and engineering problems is considerable. In present study modeling of FSW effective parameters by ANNs is investigated. To train the networks, experimental test results on thirty AA-7075-T6 specimens are considered, and the networks are developed based on back propagation (BP) algorithm. ANNs testing are carried out using different experimental data that they are not used during networks training. In this paper, rotational speed of tool, welding speed, axial force, shoulder diameter, pin diameter and tool hardness are regarded as inputs of the ANNs. Yield strength, tensile strength, notch-tensile strength and hardness of welding zone are gathered as outputs of neural networks. According to the obtained results, predicted values for the hardness of welding zone, yield strength, tensile strength and notch-tensile strength have the least mean relative error (MRE), respectively. Comparison of the predicted and the experimental results confirms that the networks are adjusted carefully, and the ANN can be used for modeling of FSW effective parameters.

1. Introduction

The AA7075-T6 aluminum alloy is one of the strongest nonferrous metals, used in various industries nowadays. High strength-to-weight ratio and its property of natural aging have led to the ever-growing use of this aluminum alloy in aerospace and high-tech industries.

7XXX series aluminum alloys are typically composed of zinc (Zn), magnesium (Mg), and copper (Cu) elements combined with aluminum (Al) as the predominant metal. The superior strength of this aluminum alloy is due to the presence of the above-mentioned alloying elements [1]. The existence of these elements in the composition of this aluminum alloy has led to the formation of AL_2CuMg and Mg_2Zn phases in the final structure. The reason for overall strength of this structure is existence of

[1] Address for correspondence: E Maleki, Mechanical Engineering Department, Sharif University of Technology-International Campus, Kish Island, Iran. Email: maleki_erfan@kish.sharif.edu/ maleky.erfan@gmail.com.

such phases [2]. The simultaneous appearance of copper and zinc increases strength, but also reduces the weld ability of this structure.

There are many articles that investigate AA7075 behavior in different conditions. Much of these articles are the studies about the investigation of mechanical properties, metallurgical properties, how to the crack growth, fatigue behavior, fatigue life and its increasing methods [3-7]. Majzoobi, et al. [8-10] surveyed the fretting fatigue behavior of Al7075-T6 considering the effects of coating and temperature in their work.

Due to having the aforementioned elements (Zn, Cu, Mg and Al) in their structure, 7XXX series aluminum alloys are highly sensitive to heat cracking in the freezing process and also to liquation cracking in the heat effected area [1, 2]. Moreover, the probability of zinc oxidation or evaporation during fusion welding of these alloy types, can be the main reason of serious problems, such as porosity or partial melting [11]. Low boiling temperatures of some elements in the structure, namely zinc and magnesium, often cause numerous problems in laser beam welding [12, 13].

Friction stir welding (FSW) is one of the non-fusion techniques of welding which has eliminated many of the defects associated with fusion welding techniques in aluminum alloy joints. In the process of friction stir welding, a tool creates frictional heat by moving along the joint line of two plates and rotating, simultaneously. It eventually creates a joint from the plasticized material. The process of welding by the FSW technique has various effective parameters including welding speed, rotational speed and axial force of the tool, tool hardness, and sizes of pin and shoulder.

Many experimental works have been done to study the usage of FSW on AA7075-T6 and investigate its parameters and characteristics. These works have survived the effect of welding parameters on microstructure, thermal, mechanical and metallurgical properties of AA7075-T6 welded joints in various conditions [14-19]. Azimzadegan, et al. [20] have investigated the effects of high rotational speeds. Rajakumar, et al. [21] and DebRoy, et al. [22] have studied the effect of tool in friction stir welded joints. Bahrami, et al. [23] have explored this process on AA7075-T6 in nano-scale.

In the case of modeling and simulation of FSW process, it can be noted to applications of numerical methods and the heuristic algorithms, which are the most-used methods in simulating and optimizing this process. The finite element method (FEM) as the most common numerical method and the simulated annealing (SA) algorithms and artificial neural networks (ANN) as heuristic algorithms have been widely employed in the simulation of FSW process. Fratini, et al. [24-26] havw provided the FEM models of FSW in their studies. He, et al. [27] have reviewed the numerical analysis of friction stir welding in their work.

Some works have employed heuristic algorithms for simulation of FSW; Babajanzade Roshan, et al. [28] have used the adaptive neural fuzzy inference system (ANFIS) models and SA algorithm to optimize friction stir welding process of AA7075 and achieve desirable mechanical properties. As mentioned, the ANNs have also been used in predicting and obtaining optimum parameters in the process of friction stir welding. Specifically, in the context of employing the artificial neural networks in predicting and optimizing the FSW process, in addition to how the network trained, the main difference is in the inputs and outputs of neural network that they have been regarded to training networks. Okuyuca, et al. [29] have evaluated the ability of neural networks in predicting the parameters of friction stir welding for aluminum plates. In their study, they took the parameters of welding speed and rotational speed of the tool as network inputs, and the parameters of yield strength, ultimate length variation of specimens, and ultimate strength of the weld as network outputs. Eventually, the results of their work showed an acceptable correspondence between the results of the neural network and those of experimental tests. In a similar study, Shojaeefard, et al. [30] have predicted the mechanical properties of non-cognate friction stir welding on AA5083 and AA7075 aluminum alloys. In their study, they used the speeds of welding and tool rotation as the inputs of the neural network and the final mechanical and metallurgical properties of the weld as the outputs of the neural network. In the end, the results of their work, likewise, showed proper abilities of neural networks for predicting the parameters of FSW process. Similarly, Yousif, et al. [31] have regarded the welding speed and rotational speed as inputs and the tensile strength, yield strength and elongation as outputs in simulation of the FSW parameters on aluminum alloy plates. Lakshminarayanan, et al. [32] gathered the welding speed, rotational speed and axial force as inputs and tensile strength as an output to survey the FSW on AA7039. Ghetiya, et al. [33] have considered tool shoulder diameter, welding speed, rotational speed, and axial force as inputs whereas the output of their modeling is the tensile strength of AA8014 welded joint. For better comparison, the used inputs and outputs of aforementioned studies about ANN application (references [29-33]) have been shown in table 1.

Table 1. The used inputs and outputs of previous works [29-33].

Reference No.	Inputs	Outputs
29	Welding speed Rotational speed	Yield strength Length variation
30	Welding speed Rotational speed	Tensile shear force hardness
31	Welding speed Rotational speed	Tensile strength Yield strength Elongation
32	Welding speed Rotational speed Axial force	Tensile strength
33	Welding speed Rotational speed Axial force tool shoulder diameter	Tensile strength

As the table 1 illustrates, the authors have regarded 2-4 inputs and 1-3 outputs in their works, while the influential parameters of friction stir welding are much more; among which tool hardness and tool pin diameter can be mentioned as inputs. Similarly, the notch-tensile strength can be considered as output. Although using fewer parameters makes the network training process faster and gives more accurate answers, it simultaneously makes the neural network responses more unrealistic in examining parameters of friction stir welding. Accordingly, this study tries not to ignore any of the influential parameters of the process, while lowering the error of network answers to its minimum by applying correct and proper values for neural networks structures. In this paper, six parameters including: welding speed, rotational speed of tool, axial force, shoulder diameter, pin diameter and tool hardness regarded as inputs of the ANN. Furthermore, four parameters including: yield strength, tensile strength, notch-tensile strength and hardness of welding zone gathered as outputs of ANN.

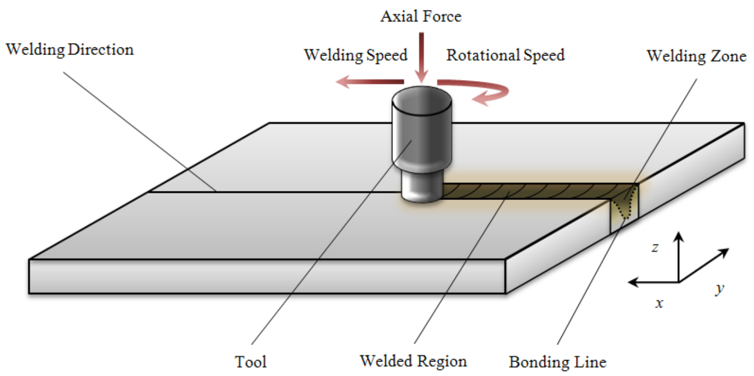


Figure 1. A Schematic of FSW.

2. Friction stir welding

Friction stir welding was invented by England's The Welding Institute (TWI) in 1991 [34]. Figure 1 shows the tools sample and a piece being welded by FSW.

In the process of friction stir welding, a tool creates frictional heat by moving along the joint line of two plates and rotating simultaneously and eventually creates a joint from the plasticized material [35].

As figure 1 demonstrates, the process of welding by the FSW technique has various effective parameters. These parameters are including the welding speed, rotational speed and axial force of the tool, tool hardness and sizes of pin and shoulder. Defects in the joints created by this technique are due to behavior of the material when it flows under welding. The material flow is in turn under the influence of the mechanical properties of the material and the tool, and the effective parameters of friction stir welding. Using friction stir welding eliminates the difficulties of fusion welding and also reduces residual stress and distortion created in the welding process [36, 37]. Table 2 presents the effective parameters in the process of friction stir welding and their mechanisms of influence.

Table 2. Parameters of friction stir welding and their influence mechanisms.

Welding Parameter	Influence Mechanism
Welding Speed	As the welding speed increases, higher work hardening is done on the joint area.
Rotational Speed	An increase in the rotational speed, increases the created heat and the intensity of stir.
Axial Force	Based on the equation $f=\mu_k F_n$,, as the axial force increases, friction increases as well, and consequently, the created heat is increased.
Tool Hardness	As the tool hardness increases, the friction coefficient between the tool and the material is increased. According to the equation $f=\mu_k F_n$, this leads to an increase in the created friction and heat.
Tool Geometry	An increase in the size of pin and shoulder, increases the contact area between tool and material. As a result, friction and heat are increased while the tool is rotating.

Investigation of welding zone and its surrounding microstructure areas demonstrate that the FSW process in welding zone affects its near areas. Figure 2 shows the typical friction stir weld in its cross-section, consisting of four main zones [38]:

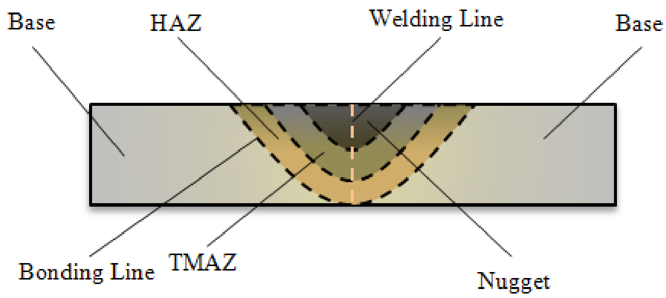


Figure 2. Typical friction stir weld in its cross-section.

- Weld Nugget (WN): stirring zone by pin rotation, fully recrystallized area.
- Heat Affect Zone (HAZ): material zone which is close to welding area, have a thermal effect but no plastic deformation.
- Thermo-mechanically Affected Zone (TMAZ): transition zone between HAZ and WN that have plastic deformation without recrystallization and thermal effect (It is usually difficult to distinguish the precise boundary between TMAZ and nugget).
- Base material (BM): the material zone that is remote from the welding area. It nearly keeps the original microstructure and mechanical properties.

Studying the influence mechanisms of the parameters, one can conclude that an increase in any of the parameters enhances the flow of material as a result of the heat increase. However, since other factors, such as the reduction of cooling rate due to the temperature rise at the beginning of the process, cannot be ignored, joint properties do not necessarily improve. It can be seen that at first increasing each of the parameters improves mechanical and metallurgical properties of the joint, and after reaching the optimum value, any further increase causes a decline in the properties.

It is observed that grain size reaches its lowest point under 5kN force, where mechanical properties are determined based on Hall-Petch equation, which is a relation between yield stress and grain size. Hall-Petch equation has been determined as follows [39]:

$$\sigma_y = \sigma_0 + k_y / d^{½} \tag{1}$$

Where σ_y is the yield stress, σ_o is material constant for the starting stress of dislocation movement, k_y is strengthening coefficient and d is average grain diameter.

3. Artificial neural networks

Artificial neural networks (ANNs) have found applications in many optimization and prediction problems in the last decade. ANNs are computational models inspired by an animal's central nervous system, in particular the human's brain, which is capable of machine learning as well as pattern recognition [40]. ANN obtains a nonlinear relation among the influential factors of a process and their corresponding outputs that, in this study, are mechanical and metallurgical properties of a joint. Therefore, a neural network enables the researcher to determine outputs for other arbitrary inputs with high accuracy. Employing ANN eliminates any need to carry out experimental tests that are costly and time-consuming. These networks are essentially simple mathematical models defining a function $\boldsymbol{f}: \boldsymbol{x} \rightarrow \boldsymbol{y}$ or a distribution over $\boldsymbol{x}$ or both $\boldsymbol{x}$ and $\boldsymbol{y}$.

Figure 3 represents a neural network. In this network, each input consists of r parameters and each output comprises s parameters. Furthermore p, w, b, f and a represent the inputs, weight matrixes, bias vectors, transfer function in neurons, and outputs, respectively.

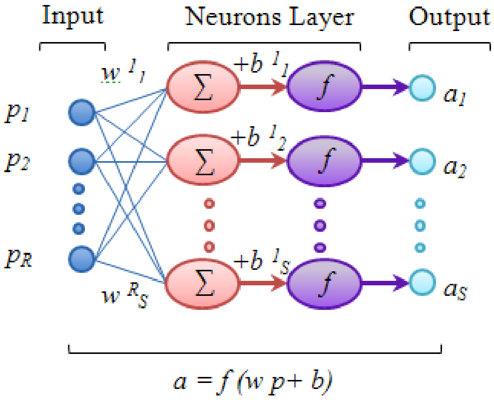


Figure 3. One layer network with R inputs and S neurons.

Based on their functions, neural networks need to be trained using a set of inputs and their corresponding outputs. Assuming one layer of neuron, training is accomplished through multiplying each input with a variant called the weight and summing it with another variant called bias before entering the neuron. The initial value of both variants can be predetermined. The obtained values from each input are summed up to form the input of the transfer function, and its output is the neuron's output that needs to compare with the experimental output value. The tangent sigmoid (Tansig) $\phi(x)$, logarithmic sigmoid (Logsig) $\psi(x)$ and linear $\chi(x)$ transfer functions are described as follows [41]:

$$\phi(x) = \frac{2}{1+e^{-2x}} - 1 \tag{2}$$

$$\psi(x) = \frac{1}{1+e^{-x}} \tag{3}$$

$$\chi(x) = linear(x) \tag{4}$$

Through the comparison, an error value is obtained. If it exceeds the permissible error value, the obtained answer is returned to the network for corrections in the weights and biases values until the desired answer is obtained. The network described above consists of one layer of neurons; however, in practice more neurons are needed to interact in parallel constructions to implement a neural network. Neural networks compose of several layers containing the neurons.

3.1. Training of ANN
The ANNs are trained with a training set of input and known output data. There is no exact available formula to decide what architecture of ANN and which training algorithm will solve a given problem and the best solution is obtained by trial and error. In the present study, the feed forward error back propagation (BP) algorithm is used for ANN training, which is the most common and efficient algorithm for training. The BP algorithm defines a systematic way to update the synaptic weights of multi-layer feed forward supervised networks. The networks composed of an input layer that receives the input values, an output layer, which calculates the neural network output, and one or more intermediary layers, so-called hidden layers. The basis of BP supervised learning process, is the gradient descent method that usually minimizes the sum of squared errors between the target value and the output of the neural network [42].

3.2. Implementation of ANN
In the implementation of ANN, there are many parameters that changing them causes alteration of the operation method, speed and accuracy of the network [42]. The number of ANN layers, the number of each layer neurons and rate of network training are some of these parameters [43]. Number of ANN layers and neurons of each layer are important parameters in deployment of ANN, since they are so effective in its operation. The significant point in using ANN is the number of layers and neurons, which are processing units of network. Increasing these parameters does not necessarily lead to speed and accuracy improved. The more complex the structure of the network is, the more time it takes. Although training time may be reduced by increasing the rate of training, if it is lower than a specific limit, speed of the network to find desirable answer will be reduced or if it is higher than a specific limit the network will become unstable. Furthermore, a considerable point in the training of the network is scattering rate of input and output parameters. If scattering of parameters is high, the network will be in trouble. In such cases by employing reasonable changes in the data, scattering is decreased and problem is resolved. In this research all values of each parameter are divided to maximum value of that parameter and normalized [44]. This action decreases scattering rate and distribution of all values between 0 and 1.

In this paper, welding speed, rotational speed of tool, axial force, shoulder diameter, pin diameter and tool hardness regarded as inputs of ANN. Yield strength, tensile strength, notch-tensile strength and hardness of welding zone considered as outputs of neural networks. Figure 4 represents an example of the conceptual structure for this ANN: 4 layers with full interconnection. Six input parameters are logged into input layer to determine four outputs.

3.3. Performance evaluation of ANN
The performance of the ANN models in predicting the FSW effective parameters are statistically evaluated using prediction score metrics. A large number of statistical criteria are available to compare the adequacy of any given model. The performance evaluation statistics used for ANN training in the present study are Pearson coefficient of correlation (PCC) and mean relative error (MRE). These parameters have been determined using the following equations:

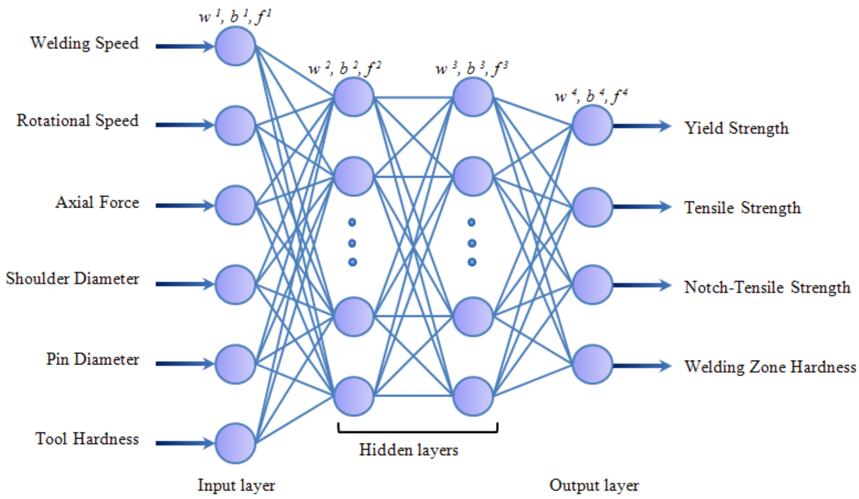


Figure 4. An example of the conceptual structure for a network.

$$PCC = \frac{\sum_{i=1}^{n}(f_{EXP,i} - F_{EXP})(f_{ANN,i} - F_{ANN})}{\sqrt{\sum_{i=1}^{n}\left((f_{EXP,i} - F_{EXP})^2 (f_{ANN,i} - F_{ANN})^2\right)}} \tag{5}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|f_{ANN,i} - f_{EXP,i}\right|}{f_{EXP,i}} \times 100 \tag{6}$$

Where:

$$F_{EXP} = \frac{1}{n}\sum_{i=1}^{n} f_{EXP,i} \text{ , } F_{ANN} = \frac{1}{n}\sum_{i=1}^{n} f_{ANN,i} \text{ , } f_{EXP} = Experimental \text{ , } f_{ANN} = \mathrm{Pr}\,edcited$$

3.4. Generating model function

After the neural network is trained successfully with four layers as it is mentioned above, the values of the four parameters of the network (*p*, *b*, *w,* and *f*) can be obtained. The function which correlates the inputs to the corresponding outputs can be calculated applying the aforementioned parameters. Finally, the model function can be determined as below:

$$\begin{aligned} a^{1} &= f^{1}(w^{1}p+b^{1}) \\ a^{2} &= f^{2}(w^{2}p^{1}+b^{2}) \\ a^{3} &= f^{3}(w^{3}p^{2}+b^{3}) \\ a^{4} &= f^{4}(w^{4}p^{3}+b^{4}) \end{aligned} \tag{7}$$

$$G\,(g(1), g(2), g(3), g(4)) = a^{4} = f^{4}(w^{4}f^{3}\,(w^{3}f^{2}(w^{2}f^{1}(w^{1}p+b^{1}) + b^{2}) + b^{3}) + b^{4}) \tag{8}$$

Where a^1, a^2 and a^3 are outputs of the first, second and third layer, respectively. a^4 is the fourth layer output which is equal to the function *G(g(1), g(2), g(3), g(4))*. The function *G* gets the values of six input parameters: welding speed, tool rotational speed, axial force, shoulder diameter, pin diameter and tool hardness. Functions of *g(1)*, *g(2)*, *g(3) and g(4)* represent yield strength, tensile strength, notch-tensile strength and hardness of welding zone as output parameters, respectively. The methodology used for neural network application in this work is as follows:

- Start
- Normalize the data (inputs & outputs)
- Feed the data to artificial neural network
- Find network optimum parameters

- Execute network training
- Obtain Pearson correlation coefficient
- If PCC ≥ 0.99 go to 8, if not go back to 4 with revising the parameters of network
- Continue processing until obtaining desired convergence between experimental and predicted values
- Obtain weights & biases values
- Create the model function
- Conduct analysis based on model function
- Verify the results using experimental values
- Calculate the error for each answer
- End

4. Experimental tests

The experimental data obtained from Rajakumar, et al. [45] work. In their study, rolled plates of 7075-T6 aluminum alloy with the thickness of 5 mm were used. Prior to the welding process, the plates were cut to the size of 150×300 mm. The welding was done perpendicular to the rolling direction. Welding was carried out in a single pass and with non-consumptive tools of several hardnesses. The hardness of tools was determined by quenching them in different materials (water, oil, air, and saltwater) in the final step of heat treatment. The chemical composition of the base metal and its mechanical properties are presented in tables 3 and 4. The joint dimensions and welding and rolling directions are shown in figure 5. Figure 6 shows the tool of FSW process.

Table 3. Chemical composition of 7075-T6 aluminum alloy (*wt* %) [45].

Material	Mg	Mn	Zn	Fe	Cu	Si	Cu	Al
AA 7075-T6	2.1	0.12	5.1	0.35	1.2	0.58	1.2	Balance

Table 4. Mechanical properties of the AA7075-T_6 [45].

Material	Yield Strength (MPa)	Ultimate Strength (MPa)	Elongation (%)	Vickers Hardness (Hv 0.05)
AA 7075-T6	410	485	12	160

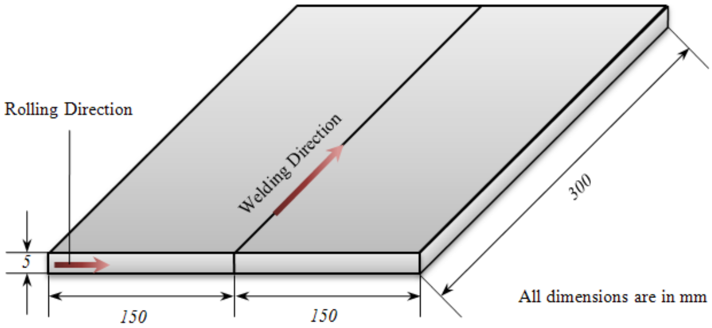


Figure 5. Square butt joint configuration.

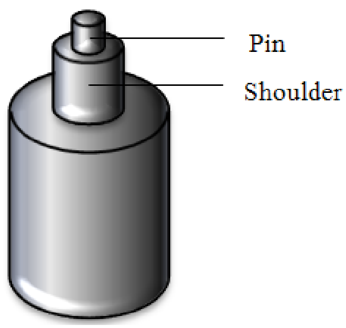


Figure 6. FSW tool.

After the welding process, the joints were cut and then machined to the desired size. In this study, American Society for Testing of Materials (ASTM E8M-04) guidelines was followed for preparing the test specimens. Two different tensile specimens were prepared to evaluate the transverse tensile properties. The smooth (un-notched) tensile specimens were prepared to evaluate yield strength and tensile strength in the cross-sectional area. Notched specimens were prepared to evaluate notch tensile strength of the joints. Figure 7 illustrates samples of these specimens with their sizes; figure 7(a)

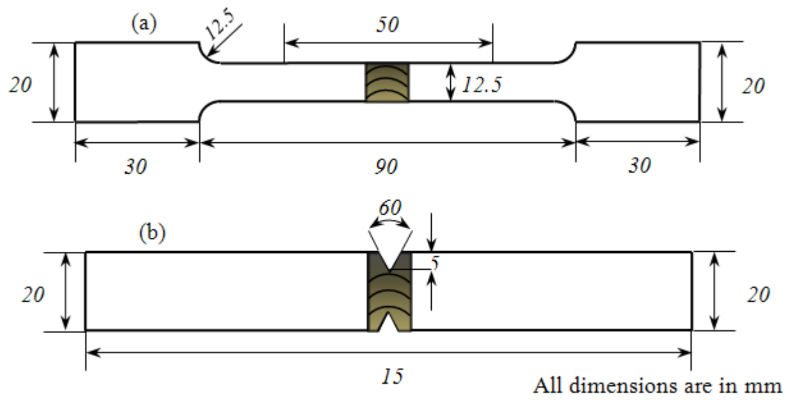


Figure 7. A machined specimens based on the ASTM standard for a) simple-tensile test, b) notch-tensile test.

Table 5. Results of experimental tests on thirty different samples [45].

Experiment No.	Rotational speed *(RPM)*	Welding speed *(mm/min)*	Axial force *(kN)*	Shoulder diameter *mm*	Pin diameter *mm*	Tool hardness *(HRc)*	Yield strength *(MPa)*	Tensile strength *(MPa)*	Notch-tensile strength *(MPa)*	Welding zone hardness *(VHN)*
1	1400	60	8	15	5	45	314	372	397	203
2	1800	60	8	15	5	45	310	334	321	185
3	1400	40	8	15	5	45	279	363	339	194
4	1400	60	8	15	5	45	310	372	393	198
5	1400	80	8	15	5	45	308	371	392	197
6	1400	60	7	15	5	45	282	321	344	180
7	1400	60	8	15	5	45	314	372	393	199
8	1400	60	8	12	5	45	280	310	333	193
9	1400	60	8	15	5	45	310	372	393	198
10	1400	60	8	18	5	45	256	271	296	197
11	1400	60	8	15	4	45	292	331	361	194
12	1400	60	8	15	5	45	310	372	393	198
13	1400	60	8	15	6	45	300	340	360	197
14	1400	60	8	15	5	40	261	283	302	186
15	1400	60	8	15	5	45	313	372	393	198
16	900	60	8	15	5	45	245	270	310	175
17	1200	60	8	15	5	45	290	310	360	191
18	1400	20	8	15	5	45	255	280	320	180
19	1400	100	8	15	5	45	245	261	283	179
20	1400	60	6	15	5	45	263	298	320	173
21	1400	60	10	15	5	45	285	286	356	171
22	1400	60	8	9	5	45	242	266	284	178
23	1400	60	8	21	5	45	296	350	312	187
24	1400	60	8	15	3	45	264	281	302	181
25	1400	60	8	15	7	45	284	321	346	178
26	1400	60	8	15	5	33	271	299	324	178
27	1400	60	8	15	5	56	282	312	336	178
28	1400	60	9	15	5	45	301	361	383	190
29	1400	60	8	15	5	50	310	368	391	192
30	1600	60	8	15	5	45	314	367	397	202

shows the smooth tensile specimen and figure 7(b) illustrates the notched specimen. Tensile tests were carried out with a 100 kN force and speed of 0.5 mm/min. Vickers micro-hardness tester was used for measuring the hardness of the weld metal with a 0.05 kg load. Table 5 presents the results obtained from the experimental tests on 30 specimens.

After the experimental tests, it was observed that increasing the tool rotational speed from 900 RPM to 1400 RPM improves the mechanical properties of the joint. Value of this parameter faces relative decline over 1400 RPM. Moreover, increasing the welding speed from 20 to 60 millimeters per minute increases the strength of specimens, and any further rise of this parameter over 60 millimeters per minute reduces specimen strength. This situation observed for all of the examined welding parameters. Optimum values for parameters of rotational speed, welding speed, axial force, tool hardness, shoulder diameter, and pin diameter were obtained as 1400 (*RPM*), 60 (*mm/min*), 8 (*kN*), 45 (*HRc*), 15 (*mm*) and 5 (*mm*), respectively.

5. Results and discussion

In this work there are two main networks: called “training network” and “testing network”. The first one is used to generate the model function. The second one used the model function to give the results of ANN. In the training network, 15 experimental test results (data of experiments 16-30) are used from the total of 30, as data sets to networks training, while in the testing network 15 different experimental data (data of experiments 1-15) which are not used during training, are used as networks testing. So the whole experimental results did not include in the training sets for modeling of FSW process on Al7075. All the input and output data for training and testing networks are normalized between 0 and 1. Table 6 shows the sample data used for networks training. For investigative purposes, 50% training data sets against 50% test data sets is obtained.

Table 6. Normalized samples data used for network training.

Sample No.	Rotational speed	Welding speed	Axial force	Shoulder diameter	Pin diameter	Tool hardness	Yield strength	Tensile strength	Notch-tensile strength	Welding zone hardness
1	0.50	0.60	0.80	0.71	0.71	0.80	0.7803	0.7258	0.7809	0.8621
2	0.66	0.60	0.80	0.71	0.71	0.80	0.9236	0.8333	0.9068	0.9409
3	0.77	0.20	0.80	0.71	0.71	0.80	0.8121	0.7527	0.8060	0.8867
4	0.77	1.00	0.80	0.71	0.71	0.80	0.7803	0.7016	0.7128	0.8818
5	0.77	0.60	0.60	0.71	0.71	0.80	0.8376	0.8011	0.8060	0.8522
6	0.77	0.60	1.00	0.71	0.71	0.80	0.9076	0.7688	0.8967	0.8424
7	0.77	0.60	0.80	0.42	0.71	0.80	0.7707	0.7151	0.7154	0.8768
8	0.77	0.60	0.80	1.00	0.71	0.80	0.9427	0.9409	0.7859	0.9212
9	0.77	0.60	0.80	0.71	0.42	0.80	0.8408	0.7554	0.7607	0.8916
10	0.77	0.60	0.80	0.71	1.00	0.80	0.9045	0.8629	0.8715	0.8768
11	0.77	0.60	0.80	0.71	0.71	0.58	0.8631	0.8038	0.8161	0.8768
12	0.77	0.60	0.80	0.71	0.71	1.00	0.8981	0.8387	0.8463	0.8768
13	0.77	0.60	0.90	0.71	0.71	0.80	0.9586	0.9704	0.9647	0.9360
14	0.77	0.60	0.80	0.71	0.71	0.89	0.9873	0.9892	0.9849	0.9458
15	0.88	0.60	0.80	0.71	0.71	0.80	1.0000	0.9866	1.0000	0.9951

To increase the accuracy of the ANNs results and the network performance, separate different networks are trained for output parameters. The input parameters in all of the networks training are the same. All of the considered input parameters, including: welding speed, the rotational speed of the tool, axial force, shoulder diameter, pin diameter and the tool hardness are used in each modeling for different output parameters.

As it is mentioned, several networks with different architectures have been trained to find the optimum structure (OS) of ANN. OS is used to predict the considered parameters with the least mean relative error possible. Results of the networks have been investigated. Table 7 demonstrates the relevant information of network structure and some related results for training networks for each considered output parameters.

Table 7. Related information of three different training networks for each considered output parameters.

Output parameter	Modeling No.	Rate of Training	Layers Structure	Hidden Transfer Function	Output Transfer Function	PCC	MRE (%)
Yield	**1**	**0.175**	**6×6×10×4**	**Logsig**	**Logsig**	**0.99899**	**0.9315**
strength	2	0.170	6×6×4×4	Tansig	Linear	0.99811	1.1261
	3	0.137	6×6×8×4	Logsig	Tansig	0.99835	0.9867
Tensile	**1**	**0.156**	**6×8×10×4**	**Logsig**	**Logsig**	**0.99976**	**0.9746**
strength	2	0.148	6×8×8×4	Logsig	Logsig	0.99913	1.0012
	3	0.124	6×6×8×4	Logsig	Tansig	0.99922	1.1553
Notch-	**1**	**0.160**	**6×8×12×4**	**Logsig**	**Logsig**	**0.99837**	**1.2127**
tensile	2	0.165	6×6×8×4	Tansig	Linear	0.98891	1.6696
strength	3	0.150	6×6×10×4	Tansig	Logsig	0.99018	1.5134
Welding	**1**	**0.112**	**6×6×12×4**	**Logsig**	**Logsig**	**0.99984**	**0.7397**
Zone	2	0.098	6×8×10×4	Logsig	Tansig	0.99979	0.7766
Hardness	3	0.120	6×6×8×4	Logsig	Linear	0.98764	0.9891

To find the ANNs optimum response, after implementation of multiple networks, some of them are noted in table 7, and investigation of them, the structures shown in table 8 are selected and used for simulation and obtaining the results.

Table 8. Information of selected networks.

Output parameter	Rate of Training	Layers Structure	Hidden Transfer Function	Output Transfer Function	Training PCC	Training MRE (%)
Yield strength	0.175	6×6×10×4	Logsig	Logsig	0.99899	0.9315
Tensile strength	0.156	6×8×10×4	Logsig	Logsig	0.99976	0.9746
Notch-tensile strength	0.160	6×8×12×4	Logsig	Logsig	0.99837	1.2127
Welding Zone Hardness	0.112	6×6×12×4	Logsig	Logsig	0.99964	0.7398

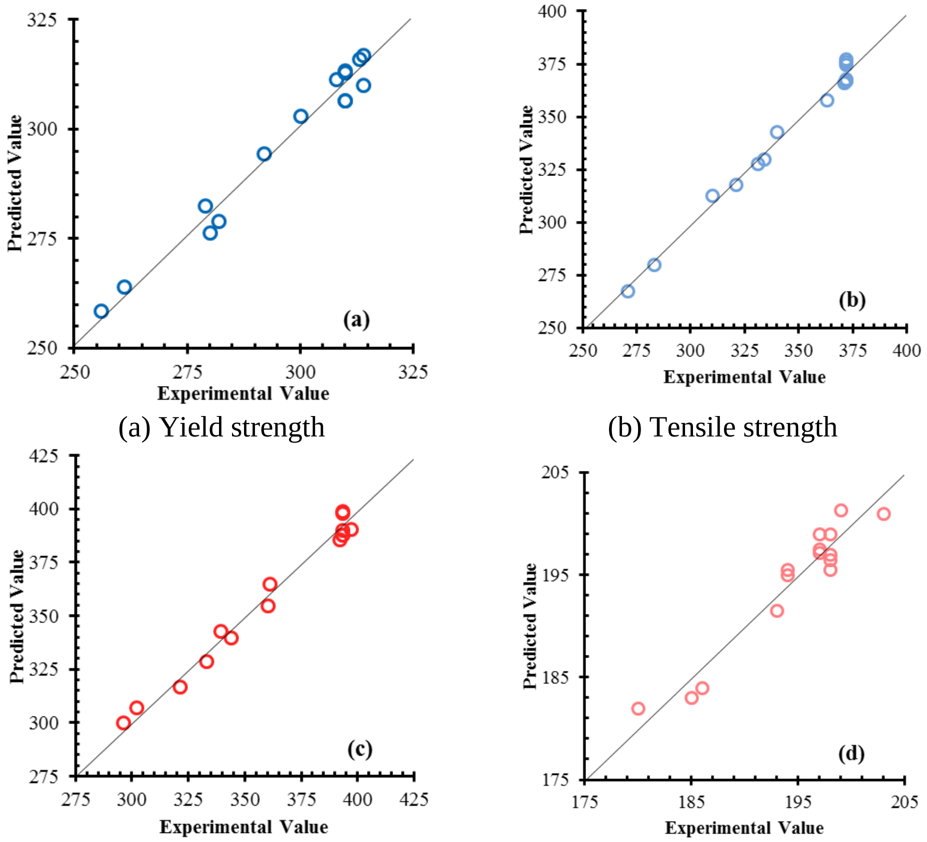
Results of table 8 show that the values of PCC and MRE are both acceptable for each output parameters, so it is concluded that networks are trained finely.

The selected networks employed to networks testing. Figure 8 demonstrates the predicted values of each output parameters by means of the obtained model function in comparison to the experimental values.

Percentage of relative error values for each fifteen testing samples, at the whole considered output parameters are shown in figure 9. Table 9 shows the achieved values of PCC and the mean relative error for testing samples by use of the selected training networks and their related model function.

As it can be seen the obtained values of PCC from testing in comparison to training, decreased; and the achieved mean relative error values from testing in comparison to training, increased. The PCC values are more than 99.9% for the hardness of welding zone and more than 99.4%, 99.5% and 99.8% for notch-tensile strength, yield strength, and tensile strength, respectively. In addition, the obtained

IOP Conf. Series: Materials Science and Engineering **103** (2015) 012034 doi:10.1088/1757-899X/103/1/012034



(a) Yield strength (b) Tensile strength

(c) Notch-tensile strength (d) welding zone hardness

Figure 8. Predicted values in comparison to experimental values for each fifteen testing samples for different considered output parameters.

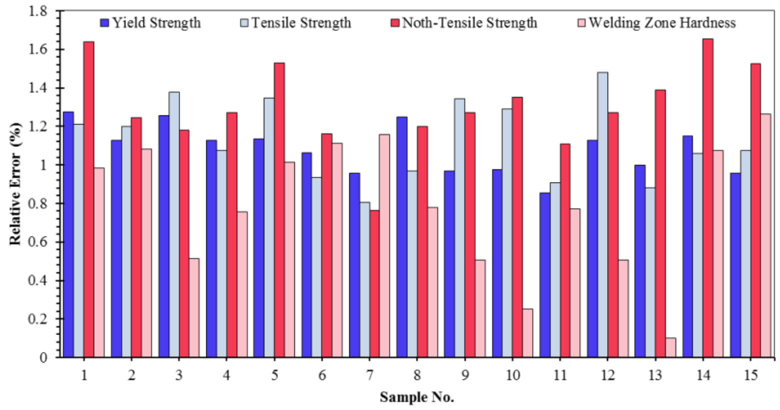


Figure 9. Obtained relative error values for each fifteen experiments of testing networks.

Table 9. Achieved values of PCC and MRE for testing networks.

Output parameter	Testing PCC	Testing MRE (%)
Yield strength	0.99543	1.0820
Tensile strength	0.99875	1.1303
Notch-tensile strength	0.99403	1.3046
Welding Zone Hardness	0.99918	0.7917

mean relative errors are in small range (0.7917-1.3046), and the predicted values for the hardness of welding zone, yield strength, tensile strength and notch-tensile strength have the least mean relative errors, respectively. According to the obtained results, it is observed that, predicted values form the response of ANN and the experimental values are in admirable agreement. So it can be concluded that the ANNs are tuned finely to predict the FSW effective parameters, and the ANNs can be used in prediction and optimization of this process parameters.

6. Conclusion

In the present study, the artificial neural networks were employed to predict the friction stir welding parameters on 7075-T6 Aluminum Alloy. The rotational speed of the tool, welding speed, axial force, shoulder diameter, pin diameter and tool hardness were regarded as inputs of the ANN. Four effective parameters of FSW process including: yield strength, tensile strength, notch-tensile strength and hardness of welding zone modeled. The obtained values of MRE are 1.0820, 1.1303, 1.3046 and 0.7917 for each parameter, respectively. Also, the values of PCC for all of the parameters are more than 99%. According to the achieved results, it can be concluded when the artificial neural networks are tuned finely, the modeling results are in admissible agreement with the experimental results. Therefore, using ANNs instead of experiments, decreases costs and the need for special testing facilities; and the ANNs can be employed to optimize and predict the effective parameters for FSW process.

References

[1] El-Shennawy M, Omar A and Masoud M 2005 Effect of Cu and Mg contents on similar and dissimilar welding of 7XXX series aluminum alloys *AEJ-Alexandria Eng. J.* **44** 715-29
[2] Balasubramanian V, Ravishankar V and Reddy G M 2008 Effect of post weld aging treatment on fatigue behavior of pulsed current welded AA7075 aluminum alloy joints *J. Mater. Eng. Perform.* **17** 224-33
[3] Jha A K and Sreekumar K 2008 Metallurgical studies on cracked Al–5.5 Zn–2.5 Mg–1.5 Cu aluminum alloy injector disc of turbine rotor *J. Fail. Anal. Prev.* **8** 327-32
[4] Nayan N, Murty S N, Mittal M and Sinha P 2009 Optimization of homogenizing mode for aluminum alloy AA7075 using calorimetric and microstructural studies *Met. Sci. Heat Treat.* **51** 330-7
[5] Ghosh R, Venugopal A, Sankaravelayudham P, Panda R, Sharma S, George K M and Raja V 2015 Effect of thermomechanical treatment on the environmentally induced cracking behavior of AA7075 alloy *J. Mater. Eng. Perform.* **24** 1-11
[6] Wang L, Daniewicz S, Horstemeyer M, Sintay S and Rollett A 2009 Three-dimensional finite element analysis using crystal plasticity for a parameter study of microstructurally small fatigue crack growth in a AA7075 aluminum alloy *Int. J. Fatigue* **31** 651-8
[7] Paturi U M R, Narala S K R and Pundir R S 2014 Constitutive flow stress formulation, model validation and FE cutting simulation for AA7075-T6 aluminum alloy *Mater. Sci. Eng. A* **605** 176-85
[8] Majzoobi G, Azadikhah K and Nemati J 2009 The effects of deep rolling and shot peening on fretting fatigue resistance of Aluminum-7075-T6 *Mater. Sci. Eng. A* **516** 235-47
[9] Majzoobi G, Nemati J, Rooz A N and Farrahi G 2006 Modification of fretting fatigue behavior of AL7075-T6 alloy by application of titanium coating and shot peening *AMPT2006 Conference* (Submitted)
[10] Majzoobi G, Sori M, Farrahi G and Hojjati R Talemi 2010 The effect of temperature on fretting fatigue behavior of Al7075-T6 *6th International Symposium on Fretting Fatigue* p 31
[11] Gupta R K, Ramkumar P and Ghosh B R 2006 Investigation of internal cracks in aluminum alloy AA0704 forging *Eng. Fail. Anal.* **13** 1-8
[12] Kou S 1987 *Welding Metallurgy* (Cambridge University Press, Cambridge)
[13] Cross C E, Olson D L and Liu S 2003 *Aluminium Welding, Handbook of Aluminum* (Dekker,

New York) vol 1
[14] Goloborodko A, Ito T, Yun X, Motohashi Y and Itoh G 2004 Friction stir welding of a commercial 7075-T6 aluminum alloy: Grain refinement, thermal stability and tensile properties *Mater. Trans.* **45** 2503-8
[15] Rafi H K, Ram G J, Phanikumar G and Rao K P 2010 Microstructure and tensile properties of friction welded aluminum alloy AA7075-T6 *Mater. Des.* **31** 2375-80
[16] Lotfi A H and Nourouzi S 2014 Effect of welding parameters on microstructure, thermal, and mechanical properties of friction-stir welded joints of AA7075-T6 aluminum alloy *Metall. Mater. Trans. A* **45** 2792-807
[17] Venugopal T, Rao K S and Rao K P 2004 Studies on friction stir welded AA 7075 aluminum alloy *Trans. Indian Inst. Met* **57** 659-63
[18] Givi M and Asadi P 2014 *Advances in Friction Stir Welding and Processing* (Elsevier, Amesterdam)
[19] Mishra R S, De P S and Kumar N 2014 *FSW of Aluminum Alloys in Friction Stir Welding and Processing* (Springer, Switzerland) pp 109-48
[20] Azimzadegan T and Serajzadeh S 2010 An investigation into microstructures and mechanical properties of AA7075-T6 during friction stir welding at relatively high rotational speeds *J. Mater. Eng. Perform.* **19** 1256-63
[21] Rajakumar S, Muralidharan C and Balasubramanian V 2011 Influence of friction stir welding process and tool parameters on strength properties of AA7075-T 6 aluminum alloy joints *Mater. Des.* **32** 535-49
[22] DebRoy T, De A, Bhadeshia H, Manvatkar V and Arora A 2012 Tool durability maps for friction stir welding of an aluminium alloy *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science* **468** 3552-70
[23] Bahrami M, Nikoo M F and Givi M K B 2015 Microstructural and mechanical behaviors of nano-SiC-reinforced AA7075-O FSW joints prepared through two passes *Mater. Sci. Eng. A* **626** 220-8
[24] Buffa G, Fratini L and Shivpuri R 2008 Finite element studies on friction stir welding processes of tailored blanks *Comput. Struct.* **86** 181-9
[25] Buffa G, Hua J, Shivpuri R and Fratini L 2006 A continuum-based fem model for friction stir welding—model development *Mater. Sci. Eng. A* **419** 389-96
[26] Fratini L, Buffa G and Shivpuri R 2010 Mechanical and metallurgical effects of in process cooling during friction stir welding of AA7075-T6 butt joints *Acta Mater.* **58** 2056-67
[27] He X, Gu F and Ball A 2014 A review of numerical analysis of friction stir welding *Prog. Mater Sci.* **65** 1-66
[28] Roshan S B, Jooibari M B, Teimouri R, Asgharzadeh-Ahmadi G, Falahati-Naghibi M and Sohrabpoor H 2013 Optimization of friction stir welding process of AA7075 aluminum alloy to achieve desirable mechanical properties using ANFIS models and simulated annealing algorithm *Int. J. Adv. Manuf. Technol.* **69** 1803-18
[29] Okuyucu H, Kurt A and Arcaklioglu E 2007 Artificial neural network application to the friction stir welding of aluminum plates *Mater. Des.* **28** 78-84
[30] Shojaeefard M H, Abdi R, Akbari M, Besharati M K and Farahani F 2013 Modeling and Pareto optimization of mechanical properties of friction stir welded AA0704/AA4703 butt joints using neural network and particle swarm optimization algorithm *J Mater Design* **44** 190-8
[31] Yousif Y, Daws K and Kazem B 2008 Prediction of friction stir Welding characteristic using neural network *Jordan J. Mech. Ind. Eng.* **2** 151-5
[32] Lakshminarayanan A and Balasubramanian V 2009 Comparison of RSM with ANN in predicting tensile strength of friction stir welded AA7039 aluminium alloy joints *Transactions of Nonferrous Metals Society of China* **19** 9-18
[33] Ghetiya N and Patel K 2014 Prediction of tensile strength in friction stir welded aluminium alloy using artificial neural network *Procedia Technol.* **14** 274-81

[34] Thomas W 1991 Friction stir butt welding (International Patent Application No. PCT/GB92/0220)
[35] Nandan R, DebRoy T and Bhadeshia H 2008 Recent advances in friction-stir welding–process, weldment structure and properties *Prog. Mater Sci.* **53** 980-1023
[36] Bussu G and Irving P 2003 The role of residual stress and heat affected zone properties on fatigue crack propagation in friction stir welded 2024-T351 aluminium joints *Int. J. Fatigue* **25** 77-88
[37] Jata K, Sankaran K and Ruschau J 2000 Friction-stir welding effects on microstructure and fatigue of aluminum alloy 7050-T7451 *Metall. Mater. Trans. A* **31** 2181-92
[38] Threadgill P, Leonard A, Shercliff H and Withersd P 2009 Friction stir welding of aluminium alloys *Int. Mater. Rev.* **54** 49-93
[39] Hall E O 1951 *Proc. Phys. Soc. Lond. B* **64** 747-53
[40] Chen S C, Lin S W, Tseng T Y and Lin H C 2006 Optimization of back-propagation network using simulated annealing approach *IEEE International Conference on Systems, Man and Cybernetics* (IEEE, Taiwan) pp 2819-24
[41] Vogl T P, Mangis J K, Rigler A K, Zink W T and Alkon D L 1988 Accelerating the convergence of the back propagation method *Biol. Cybern.* **59** 257-63
[42] Niyati M and Moghadam A M E 2009 Estimation of products final price using bayesian analysis generalized poisson model and artificial neural networks *J. Ind. Eng*. **2** 55-60
[43] Maleki E and Sherafatnia K 2016 Investigation of single and dual step shot peening effects on mechanical and metallurgical properties of 18CrNiMo7-6 steel using artificial neural network *Int. J. Mater. Mech. and Manufac.* **4** 100-5
[44] Mendelsohn L 1994 MATLAB neural network toolbox *Technical Analysis of Stocks & Commodities* pp 12
[45] Rajakumar S, Muralidharan C and Balasubramanian V 2011 Influence of friction stir welding process and tool parameters on strength properties of AA7075-T6 aluminum alloy joints *J Mater Design* **32** 535-49