Experimental Study and Modeling of Friction Stir Welding Process of Aluminum 1100 Alloys, Using Artificial Neural Network with Taguchi Method

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Abstract: In this paper, the temperature distribution in workpiece and microstructure of welded zone in friction stir welding of aluminum 1100 alloys and the effect of the tool rotational speed on these parameters have investigated experimentally. Also feed forward back propagation neural network has been used to predict the temperature of the workpiece during the welding process by considering the process time and tool rotational speed as input parameters of the neural network. For this purpose, the Taguchi design of experiments has been used and the network with minimum mean squared error was selected. This way of neural network selection is very formal and effective than the existing methods. The selected network mean squared error with this approach is 0.000388, its most differences with experimental inputs is 0.770997ºC and its regression R values is 0.99113. Also according to experimental results, increasing tool rotational speed leads to higher plastic deformation in materials and also causes increasing the friction between tool and workpiece which leads to higher workpiece temperature.

Keywords: Artificial Neural Network, Friction Stirs Welding, Microstructure, Taguchi Method, Tool Rotational Speed, Workpiece Temperature Predicting,

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1 INTRODUCTION

Friction stir welding process was invented in 1991 and its main purpose was creating a bond between materials which these welding with fusion methods were difficult. This process tool has two important parts, shoulder and pin .The shoulder is in contact with workpiece surface during process and with creating friction and provides required heat to make material plastic and pin causes hard plastic deformation of materials [1-3]. The structure obtained by this process is created from re-crystallized fine grains due to hard plastic deformation at high temperature which improves mechanical Properties [4], [5]. There are no defects which can occurs during casting and solidification process in FSW, because materials are not melted and welding process occurs in plastic state, but the creation of some other defects such as tunnel hole and cracks in the structure is possible [5].

Khodir et al. [6], welded aluminum 7075 and 2024 alloys to each other using friction stir welding method, and investigated the effects of welding speed and locating of sheets at advancing side or retreating side on mechanical properties of obtained weld. Zhang et al. [7], studied the relationship between feed rate and defects created during friction stir welding of magnesium AZ31 alloy. kostka et al. [8], bonded aluminum 6064 alloy to magnesium AZ31 alloy using friction stir welding process and it resulted that fine – grained Al12Mg17 and Nano- grained Al13Mg2 phases were generated in welding area.

Elangovan et al. [9], investigated the effects of different shapes of pin and resulted that the structure with no defects and better properties can be achieved using square pin. Rhods et al., [10], in their study about the obtained weld microstructure in friction stir welding of aluminum 7075 alloy to titanium 651 alloy, showed that dissolution of bigger sediments and deposition of them are occurred in the center of weld. Also they concluded that the highest temperature of workpiece reaches to 480-400ºC during process. Murr et al., [11, 12], studied friction stir welding of aluminum 6061 alloy and concluded that workpiece temperature reaches to higher than 400ºC.

Benavides et al., [13], investigated the effects of workpiece temperature on grain size in friction stir welding process of aluminum 2024 alloys. They reported that decreasing workpiece temperature from 30 to -30ºC in the beginning of process by liquid nitrogen, causes reducing workpiece peak temperature from 330 to 140ºC in 10 mm around weld central line and so decreases the grain sizes from 10 to 0.8 µm. Selection of artificial neural network with optimum parameters which is a powerful method for modeling of various issues is a process which takes a lot of time and regarding this subject, it is possible to use design of experiments method in this field. Tortum et al., [14], used Taguchi design of experiments method to choose the artificial neural network model with optimum operation. They chose the number of neurons in first and second layers, type of neural network activation function, percent of information used in training part and type of normalize function of data as the inputs factors of design of experiments.

Pontes et al., [15], used Taguchi design of experiments method to design artificial neural network parameters for prediction of surface roughness in lathing process. Ko et al. [16], used the combination of results obtained by metal forming process simulation and Taguchi design of experiments as the training information in artificial neural network. Khaw et al., [17], used Taguchi design of experiments method to choose optimum parameters for artificial neural network to increase the training artificial neural network speed and accuracy.

In this research, the aluminum 1100 alloy was selected for friction stir welding process and the temperature distribution in workpiece and the effects of tool rotational speed on temperature distribution was investigated by performing some experiments. Also the microstructure of welded samples was studied. Then the temperature during friction stir welding process was modeled using feed forward back propagation neural network considering the time and tool rotational speed as inputs of network. Also the Taguchi design of experiments method with number of neurons in hidden layer, type of training function and type of transfer function of hidden layer as the inputs parameters and mean squared error which is obtained from artificial neural network as the output parameter, was used to present the best model by artificial neural network to predict workpiece temperature in friction stir welding process.

2 EXPERIMENTS

2.1. Experimental setup

In this research a milling machine with a designed fixture on its bed (to fix the workpiece) was used as welding machine. This welding machine is shown in figure 1.

2.2. Experiments procedure

In this investigation the workpiece temperature during friction stir welding process of aluminum 1100 alloy and the effects of tool rotational speed was investigated. Also the microstructure of welded zone and the effects of tool rotational speed on microstructure of welded zone and the size of generated gains were studied. Tool rotational speeds used in this study are 900, 1120 and 1400 rpm (clockwise), while tool feed rate was fixed at 280 mm/min. To investigate the obtained weld microstructure, metallographic samples was prepared and VEGA-TESCAN-LMU optical microscopy was used. The workpiece temperature in 10 mm around weld center line was recorded using 5 K-type thermocouples which were fixed on certain places on workpiece, in 5 second intervals, during welding process according figure 1. To investigate the welding parameters on workpiece temperature, the average of results of 5 thermocouples was calculated.

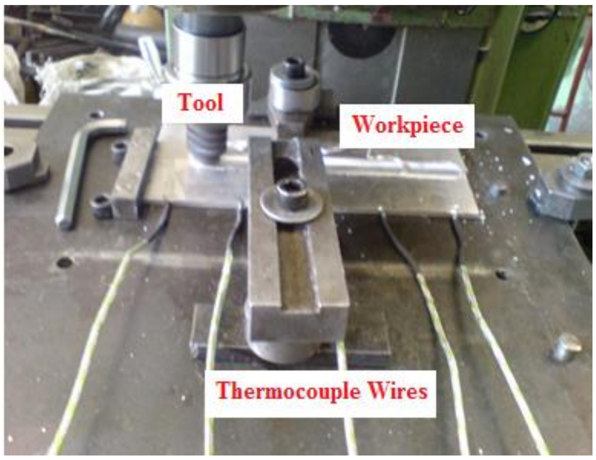

Fig. 1 The Welding machine used in this research with attached thermocouples on workpiece

2.3. Experiments materials

2.3.1. Workpiece

The workpiece in this research was a sheet of aluminum 1100 alloy in 500×75 mm dimension with 5 mm thickness. The workpiece chemical composition is shown in table 1.

Table 1 Chemical composition of workpiece

Element	Al	Si	Fe	Mn	Cr
Wt %	99.3	0.138	0.182	0.016	0.03

2.3.2. Tool

Considering that in friction stir welding process, the tool pin has much contact with workpiece in comparison with tool shoulder, the pin has more potential to wear in high temperature so the shoulder and pin was made separately and then assembled to each other according figure 2. Tool shoulder was made from 2344 hot work steel and has a central hole which tool pin is passed through it. Tool pin is 6×6 mm bullion made from HSS steel which is embedded in tool shoulder. The designed grooves on tool body are for increasing heat transfer to out. The height of pin was adjusted to 4.8 mm from edge of shoulder and the diameter of tool shoulder was 20 mm. The tool body hardness was reached to 52 Rockwell C by heat treating operations after machining. Also tool edge deviation from vertical line was considered 3º while tool shoulder was penetrated 0.5 mm to workpiece.

Fig. 2 The FSW tool used in this study

3 ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network is an idea to process information which is inspired from biological nervous system and process the information like brain. The system consists of a large number of interconnected processing elements which is called neurons which act for solving a problem coordinately. An artificial neural network is adjusted during a learning process to do a certain task like patterns recognition and classify information.

Neural network, works with examples and they cannot be programmed to perform a specific task. Advantage of neural network is that it finds out how to solve the problem. Each neural network should be trained to have desired performance [18], [19]. Model of an artificial neuron is shown in figure 3. Input vector to this neuron in fact is outputs of other neurons (x1,x2,…,xn) considering the relative weights (w1j, w2j,…,wnj). The amount of total input to neuron j will be gotten using equation 1.

$$Net_j = \sum_{i=1}^{n} x_i \times w_{ij} \tag{1}$$

Where the xi is the output of neuron i and w_{ij} is 7 the weight between neuron i and j and Net_j is total input amount of neuron j. In other words, O_j is output of neuron i, and is the function of total amount of inputs of this neuron which the type of this function represents performance of this neuron. In Fig. 3, F is transfer function and W_0 is threshold amount which is usually zero [20].

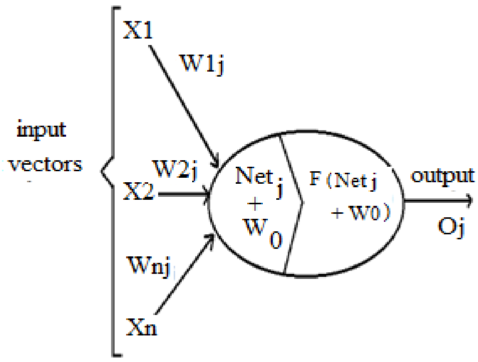

Fig. 3 A neural network model

3.1. Feed forward back propagation neural network

Feed forward neural networks which are useful in modeling of different problems are formed from neurons in different layers. First layer is input layer and last layer is output layer where the middle layers are hidden layer. Each neuron in special layer has relation with all of neurons in next layer. Relation between neuron i and neuron j is adjusted with weight coefficient (W_i), as the weight coefficient represents the importance of this relationship in neural network. Fig. 4 shows feed forward back propagation neural network with three layers. In back propagation networks, the weights of last layer are corrected firstly and then the previous layers weights are corrected after specifying network outputs. In these networks, each layer neurons are connected with neurons of next layer, only [21].

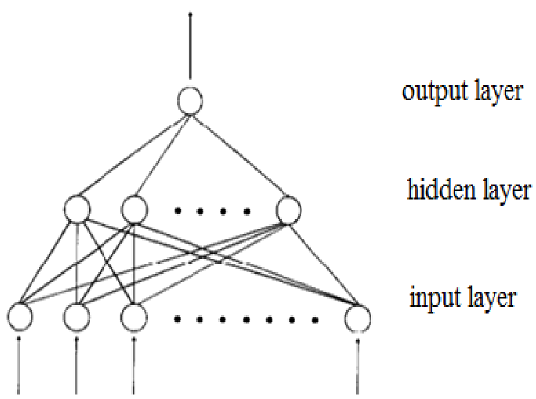

Fig. 4 Schematic of Feed forward back propagation neural network with 3 layers

In this study a feed forward back propagation neural network with three input, hidden and output layers was used to model the FSW process. The process time and tool rotational speed were considered as inputs of network and workpiece temperature during friction stir welding was considered as output of network while 70% of data was used for network training and 30% for testing, from 68 available experimental data, where the transfer function of output layer was “purelin”. The feed forward back propagation neural network was programmed in Matlab software and the network with optimum performance was selected using Taguchi design of experiments method. Also Eq. (2), was used to normalize the data (between 0.1 to 0.9) because using row input data, decreases the speed and accuracy of network. The normal network output was obtained by inverting the normalizing algorithm (equation 2), finally.

$$N_i = 0.8\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) + 0.1 \qquad (2)$$

4 DESIGN OF EXPERIMENTS

4.1. Definition of the design of experiments

Design of experiments can be defined as making changes in process inputs to observe changes in process outputs. Some of the aims of design of experiments are improving quality, reduction of wasted materials, improving process performance and increasing productivity. Other objectives of design of experiments are reducing the number of experiments and so decreasing the time and cost of experiments, determining the variables that have the most effect on process outputs, removing unnecessary parameters, calculating the percent influence of each variable and determining the errors and the optimum conditions [22].

4.2. Taguchi method of design of experiments

In the late 1940s, Doctor Taguchi introduced new statistical concepts and after some years it was proved that this concept is valuable in subject of control and improving quality. Taguchi method is quite different from common quality engineering. Taguchi method emphasizes on the quality design during design of products while other methods of design of experiments are based on the inspection and quality control during production or post-production process. Taguchi uses orthogonal arrays to reduce the number of tests greatly. These arrays with special features are selected from total number of full factorial experiments [23].

The input parameters of performed design of experiments by Minitab software with their levels are shown in table 2. Also in the performed Taguchi analysis in this paper, the mode was set on “smaller is better” because the mean square error obtained from neural network should be minimum.

Table 2 Input parameters in Taguchi design of experiments with their levels

Levels Parameters	1	2	3	4	5	6
Number of neurons in hidden layer	5	10	15	20	25	30
Training function	trainlm	trainr	traingd	-	-	-
Transfer function of hidden layer	logsig	purelin	tansig	-	-	-

5 RESULTS AND DISCUSSION

5.1. Temperature distribution

Figure 5, shows temperature distribution in workpiece. According to this figure, the workpiece temperature increases gradually with the progress of the welding process which is due to preheating of points in front of weld line with welding of earlier points.

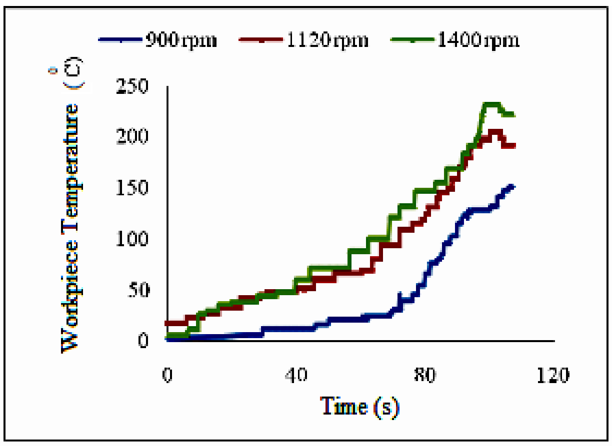

Fig. 5 Effect of tool rotational speed on temperature distribution in workpiece (feed rate = 280 mm/min)

5.1.1. Effect of tool rotational speed on temperature distribution

Figure 5 shows the effect of tool rotational speed on temperature distribution of workpiece. According to this figure, workpiece temperature is increased by increasing tool rotational speed. Increasing tool rotational speed leads to higher friction between the tool and workpiece and also higher plastic deformation of material in weld zone which increases workpiece temperature.

5.2. Microstructural study

Since the amount of alloying elements of aluminum 1100 alloy is insignificant and secondary phases such as sediments and dendrite structure is not observed in its structure, in this respect, significant changes in the microstructure is related to the morphology and particle size, generally.

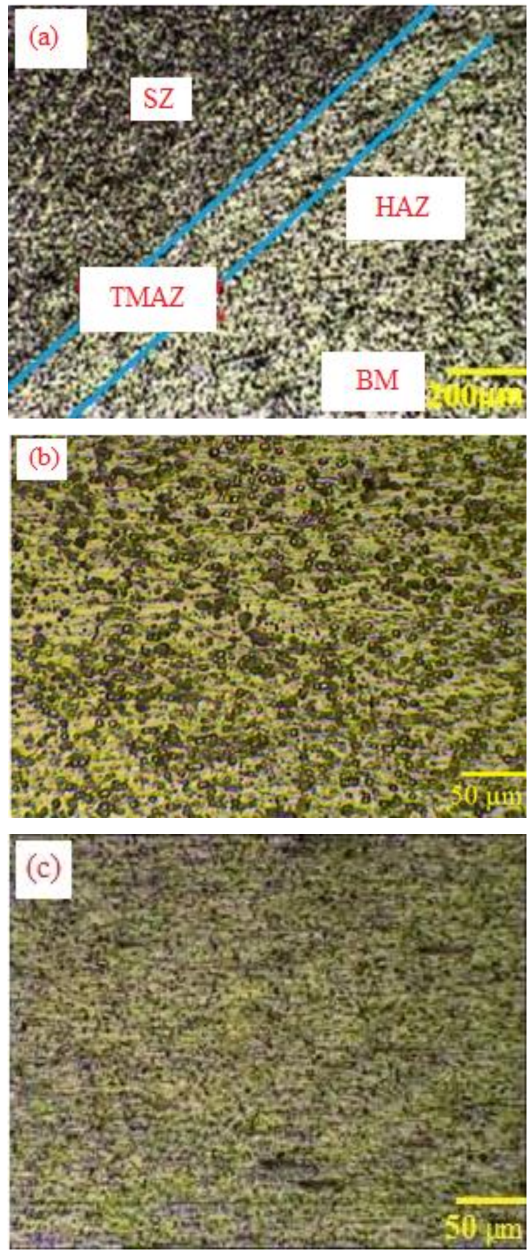

Fig. 6 **(a)** Cross section view of weld obtained by friction stir welding and different regions around weld area, (b) base material microstructure, (c) nugget zone microstructure

Figure 6a, shows the magnified cross section view of weld obtained by friction stir welding of aluminum 1100 alloy. According to figure 6a, the stir zone or nugget zone, thermo-mechanically affected zone and heat affected zone beside base material are observed. According to figure 6a, the grains in stir zone are extremely fine and homogeneous and this region has uniformed microstructure due to dynamic re-crystallization which is followed by severe plastic deformation occurred in stir zone. The grains in thermo-mechanically affected zone have particular orientation which has been drawn to the longitudinally in boundary between stir zone and heat affected zone. However the plastic deformation does not occur in heat affected zone, but the obtained heat by welding changes the mechanical properties of this area in comparison to base material while the gains size in this area is similar to base material. Figures 6b and 6c show microstructure of base material and nugget zone in higher magnification. Reducing the grains size in nugget zone compared to base material is clearly visible according to figures 6b and 6c.

5.2.1. Effect of tool rotational speed on microstructure

Figure 7 shows the effect of tool rotational speed on microstructure and grains size in stir zone. According to this figure, the grains size in stir zone is enhanced by increasing tool rotational speed from 900 rpm to 1400 rpm. The amount of generated heat by friction and plastic deformations of materials is enhanced by increasing tool rotational speed and this leads to grains growth during re-crystallization.

5.3. Taguchi design of experiments in neural network modeling

In order to select the optimum neural network, the Taguchi design of experiment method was used. The performed design of experiments in this study is shown in Table 3. According to Table 3, the number of neurons in the hidden layer of neural network in 6 levels and type of training function and transfer function of hidden layer of neural network, in 3 levels, were considered as input parameters and a L18 Taguchi orthogonal array was designed for this purpose. Also the output parameter of Taguchi design of experiment was mean square error obtained by artificial neural network. Also, the tool rotational speed and the progressing time of friction stir welding process were considered as inputs of feed forward back propagation neural network and workpiece temperature during the welding process was considered as output of the neural network. For each test of table 3, the neural network with defined parameters in Taguchi design of experiments showed in table 3, was implemented in Matlab software and repeated 5 times. The mean square error obtained by neural network in 5 replicate was measured and the average was considered as output parameter of Taguchi design of experiments method. Table 4 shows these results.

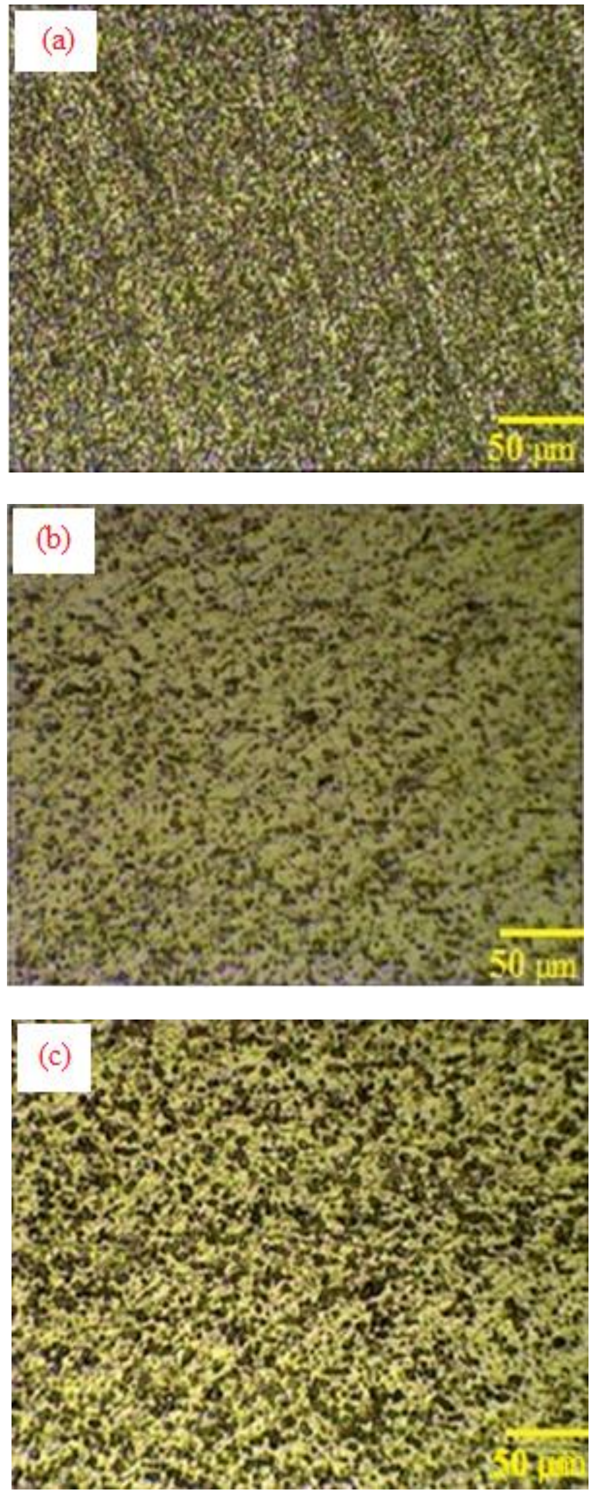

Fig. 7 Microstructure of stir zone in 280 mm/min feed rate and different tool rotational speed, (a) 900 rpm, (b) 1120 rpm, (c) 1400 rpm

Table 3 The performed design of experiments in this study

Factor	Number of neurons in hidden layer (A)	Type of training function (B)	Type of transfer function o hidden layer (C)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	1
5	2	2	2
6	2	3	3
7	3	1	2
8	3	2	3
9	3	3	1
10	4	1	3
11	4	2	1
12	4	3	2
13	5	1	2
14	5	2	3
15	5	3	1
16	6	1	3
17	6	2	1
18	6	3	2

Table 4. The results related to mean square error in 5 replicate artificial neural network implementations for 18 designed cases by Taguchi design of experiments method

Test	MSE_1	MSE_2	MSE_3	MSE_4	MSE_5	MSE (average)
1	0.000513	0.057738	0.000513	0.000512	0.000440	0.011943
2	0.003044	0.003218	0.003191	0.003191	0.003140	0.003157
3	0.015344	0.083054	0.0618	0.061836	0.015388	0.047484
4	0.000577	0.125699	0.000479	0.000479	0.000479	0.025542
5	0.003176	0.00325	0.003022	0.003022	0.002996	0.003093
6	0.039769	0.011588	0.004486	0.004486	0.00375	0.012816
7	0.000504	0.00308	0.003098	0.003098	0.0031	0.002576
8	0.000725	0.000608	0.000706	0.000707	0.000595	0.000668
9	0.111552	0.0176	0.102035	0.102	0.0298	0.072597
10	0.000397	0.000345	0.000428	0.000396	0.000396	0.000392
11	0.001019	0.001189	0.001008	0.000906	0.000604	0.000945
12	0.003800	0.00349	0.004218	0.00349	0.00333	0.003665
13	0.003079	0.00303	0.003271	0.00325	0.003034	0.003133
14	0.000520	0.000602	0.000549	0.000617	0.000497	0.000557
15	0.061027	0.034796	0.006554	0.0218	0.015398	0.02791
16	0.039769	0.000307	0.000387	0.000233	0.000233	0.008186
17	0.000624	0.002410	0.000819	0.00104	0.000677	0.001114
18	0.004178	0.00319	0.003261	0.0042	0.003892	0.003744

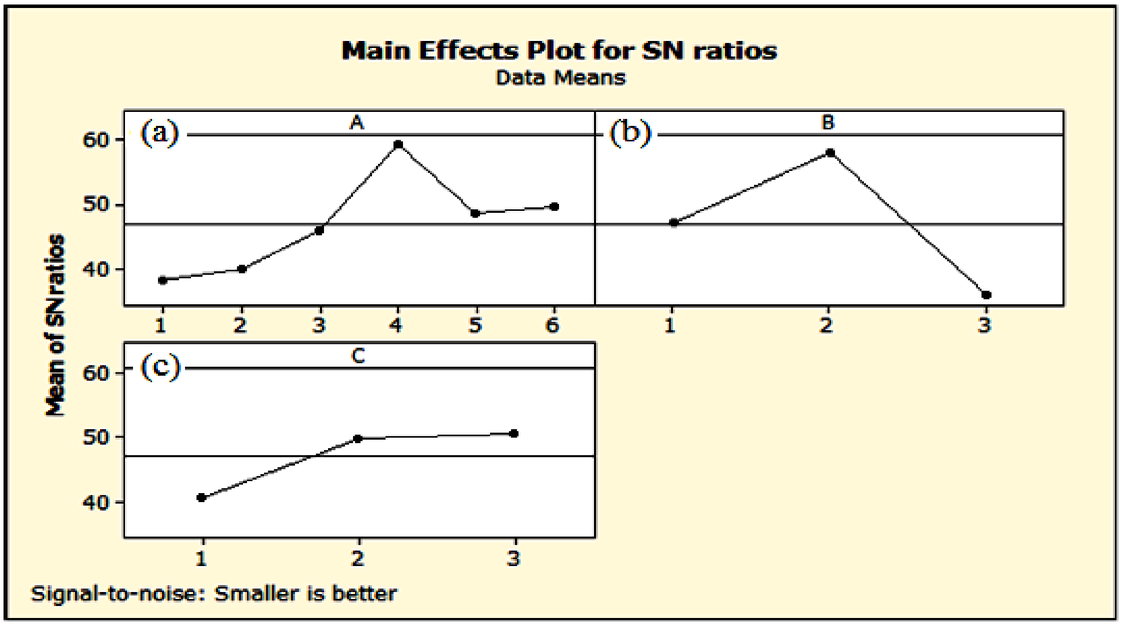

Fig. 8 S/N ratio plots of Taguchi design of experiments

5.3.1. The S/N ratio plots of Taguchi design of experiments method

The S/N ratio (signal to noise ratio) plots related to the effects of input parameters on outputs parameters in Taguchi design of experiments method is shown in figure 8. According to figure 8a, increasing the number of neurons in hidden layer of neural network up to 20 neurons, leads to enhancing S/N ratio plot, but it is decreased by increasing the number of neurons more than 20 and the best network performance occurs when there are 20 neurons in the hidden layer. Figure 8b shows that the best network performance happens when using TRAINR function as the training function. Also as shown in figure 8c, using TANSIG function as the transfer function of hidden layer of neural network leads to the best performance. Also as shown in Figure 8, the best performance of neural networks is obtained by choosing forth level of first factor (20 neurons in hidden layer of neural network), second level of second factor (TRAINR function as training function) and third level of third factor (TANSIG function as transfer function of hidden layer), and therefore these levels of input parameters are used as optimal levels in artificial neural network to model and predict the workpiece temperature during friction stir welding process considering with tool rotational speed and process time as input parameters of neural network.

5.3.2. Analysis of variance in Taguchi design of experiments

Performed analysis of variance in Taguchi design of experiments is shown in table 5. As shown in table 5, which shows the amount of P value for input factors of Taguchi design of experiment, all of input factors have great importance in influencing the output parameters of design of experiments.

Table 5 Table of analysis of variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	5	865.3	865.3	173.05	3.26	0.067
B	2	1471.8	1471.8	735.89	13.88	0.003
C	2	370.3	370.3	185.16	3.49	0.081
Residual Error	8	424.1	424.1	53.01		
Total	17	3131.4				

5.4. Application of feed forward back propagation neural network

According to the results of design of experiments method and selecting neural networks with optimal performance (with minimum mean square error), this network is used to predict the temperature of workpiece in friction stir welding process of aluminium 1100 alloys with acceptable accuracy. Table 6, shows the mean square error obtained by implementation of optimum neural network with 5 replicate and their average.

Table 6 Results of neural network in optimum condition

MSE1	MSE2	MSE3	MSE4	MSE5	MSE (average)
0.000359	0.000363	0.000414	0.000429	0.000375	0.000388

Selected optimum neural network which also performs regression in different stages of training, validation and testing; has good R value according to figure 9 and total R value of this regression is 0.9913.

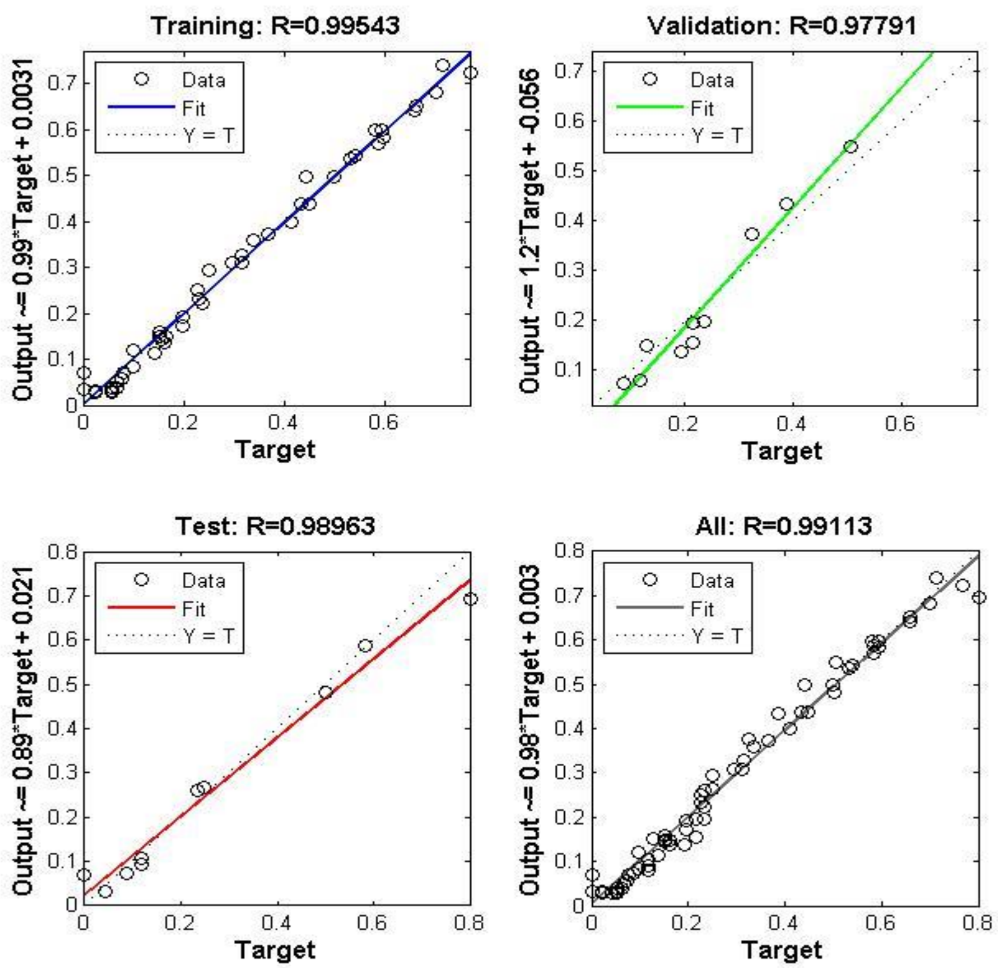

Fig. 9 Regression of optimum neural network

6 CONCLUSION

In this study, the workpiece temperature during friction stir welding process of aluminium 1100 alloy and microstructure of the welded samples was investigated and the effects of tool rotational speed on workpiece temperature distribution, the welded microstructure and grains size of the welded samples was studied. Also the feed forward back propagation neural network with Taguchi design of experiments method was used to model the workpiece temperature during friction stir welding process. The results of this study are as below:

a) The workpiece temperature increases with progress of the welding process gradually because of preheating of front points of weld line due to welding previous points.
b) The workpiece temperature is increased by increasing tool rotational speed.
c) Due to the dynamic re-crystallization occurred in stir zone, the grains size in this region decreases and uniform and homogeneous structure is obtained.
d) The amount of generated heat by friction and plastic deformation is enhanced and the grains size in stir zone is increased by increasing tool rotational speed from 700 to 1400 rpm.
e) Considering the number of neurons in hidden layer of neural network, type of transfer function of hidden layer and type of training function of artificial neural network as input parameters and mean square error obtained by artificial neural network as output parameter of Taguchi design of experiments method, the optimum feed forward back propagation neural network (with minimum mean square error) is selected to model and predict workpiece temperature during the welding process of aluminium 1100 alloy.
f) The obtained optimum neural network with time and tool rotational speed as input parameters for predicting the workpiece temperature during FSW process, has acceptable accuracy as the mean square error was 0.000388, the greatest difference with the experimental data was 0.770997°C and the R value in regression analysis was 0.99113.

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