Application of Artificial Neural Network to Friction Stir Welding Process of AA7050 Aluminum Alloy

Aniket K. Dutt, K. Sindhuja, Siriyapureddy Vijaya Narasimha Reddy, and Pawan Kumar

Abstract In the present study, an artificial neural networks (ANN) model is developed for the analysis and correlation between friction stir welding (FSW) parameters, namely traverse speed and rotation rate with mechanical properties. The study focuses on FSW of precipitation strengthened AA7050 aluminum alloys. FSW generates enormous heat and strain, which modify the microstructure of AA7050 alloy. In AA7050 alloy, the precipitation of strengthened phase depends on peak temperature achieved during the FSW process and peak temperature depends on FSW parameters. The input for the ANN simulation is FSW parameters and output is the weld metal hardness and heat affected zone (HAZ) hardness, peak temperature of weld nugget, and peak temperature of HAZ. The simulated results showed agreement with the literature data.

Keywords FSW process · ANN · Aluminum alloy · Thermal cycle

1 Introduction

Friction stir welding (FSW) process is a solid-state welding process and used for various alloys including aluminum alloys, magnesium alloys, titanium alloys and steel [1]. Figure 1 represents the typical FSW process. Two materials are joined using the FSW process. Initially, materials are clamped properly on FSW platform followed by insertion of tool into the workpiece and traverse along the weld direction. The tool has two important features: pin and shoulder. The pin portion inserted completed into the workpiece and the shoulder area contacts to the workpiece surface. The heat is generated due to tool and material friction. The generated heat softens the material and tool rotation results in material flow. There are two main FSW process parameters, namely rotation rate and welding speed. The FSW process parameters modify the microstructure, which improves the mechanical properties. The invention

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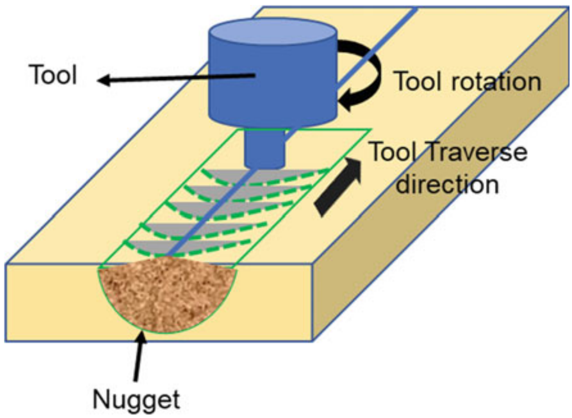
Fig. 1 Typical FSW process



of the FSW process by TWI, UK, was done for solid-state joining [2]. The application of aluminum alloys is in the field of automobile, aircraft, and various other industries.

7XXX series are precipitation strengthened alloys and it is established that 7050-T7451 is strengthened due to the presence of coherent η' phase [3]. A general precipitation sequence in most of 7XXX series alloy is

SSSS → Clusters → GP Zones → η' → η

The precipitation of η' and η phases depends on the peak temperature attained during the FSW process [3]. Coherent η' phase strengthened the alloy more compared to incoherent η phase. The dissolution of strengthening phase starts at a temperature above 190 °C. The η phase precipitates between 215 and 250 °C. Above 250 °C, it starts coarsening and begin to dissolve at 320 °C. The hardness of heat affected zone of 7050 alloy is minimum as the temperature exist in the range of 300–350 °C. Hwang and Chou observed the minimum hardness of 7075 weld for thermal cycle, which peak temperature is 377 °C. This is attributed to dissolution of η phase. The strength or hardness of 7050 alloy is related to the size of phases and their fractions [4]. The η' phase possesses an HCP crystal structure. The size of η' phase is 3–4 nm in thickness and 5–10 nm in width, whereas η phase is incoherent and cigar-like structure.

The ANN has become very important research fields for engineering in last two decades. With the advancement of computer technology, it is becoming more popular [5, 6]. ANN possesses the ability to determine the complex relationships between inputs and outputs. In recent years, few authors performed ANN on friction stir welding on aluminum alloys [7–11]. Lakshminarayanan and Balasubramanian [10] performed ANN on AA7039 alloy to predict the tensile strength. Okuyucu et al. [7] performed ANN to FSW of Al plates to predict mechanical properties.

In the present study, application of ANN to the FSW of AA7050 alloys has been investigated to predict the hardness of heat affected zone (HAZ), the hardness of weld metal, the peak temperature of HAZ, and peak temperature of weld metal.

2 Materials and Method

The ANN is performed on the AA7050 alloy. The composition of AA7050 alloy is tabulated in Table 1.

The input data for ANN simulation has taken from the literature and shown in Figs. 2 and 3. The hardness of weld nugget and HAZ in terms of welding speed and rotating speed are as shown in Fig. 2. The peak temperature of the thermal cycle of weld nugget and HAZ in terms of welding speed and rotating speed is as shown in Fig. 3.

ANN solves complex problems using computational models. It has three layers, namely input, hidden, and outer layers. The input layers consist of input parameters.

Table 1 Weight percent of AA7050

Element	Zn	Mg	Cu	Zr	Al
wt%	6.2	2.35	2.3	0.1	Remaining

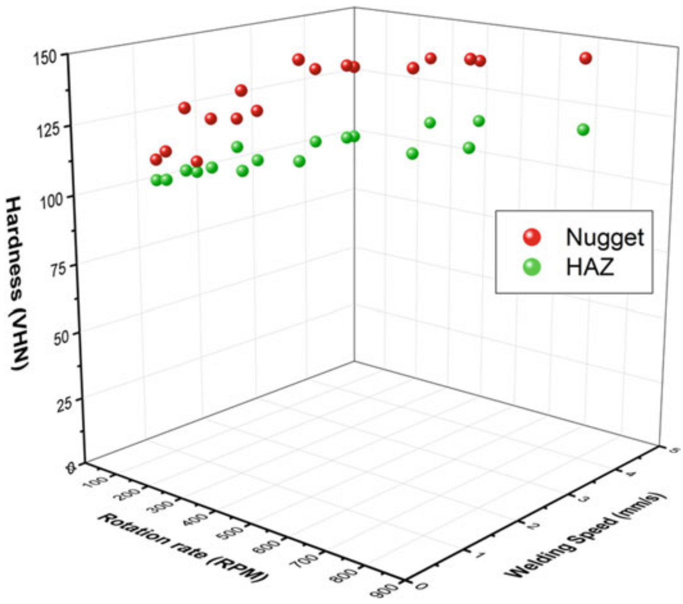


Fig. 2 Hardness of nugget and HAZ zone with respect to welding speed and rotation rate

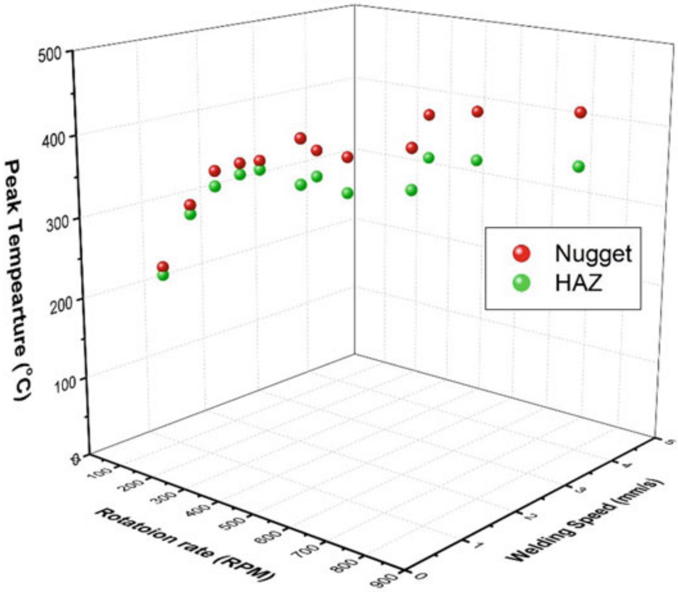


Fig. 3 Peak temperature of nugget and HAZ region with respect to welding speed and rotation rate

The FSW parameters are input parameters in the present study. The information of input layer is passed to the hidden layer following to output layers. A neuron is a basic unit of ANN and it relates to each other by synapses. Each synapse relates to weight. Different weights and bias are provided. A two-layer feed-forward network has applied with sigmoid hidden neurons and liner output neurons. The training, validation, and testing data are kept as 70%, 15%, and 15%, respectively. In the training step, data are provided to network for training and network is adjusted based on the error function. During the validation step, training is halted, and network generalization is measured. In the testing step, independent measure of network performance is performed during and after the training. Levenberg–Marquardt backpropagation algorithm is used to train network. The ANN is performed on three different numbers of hidden layers. These three neural networks are as follows: 2-1-1, 2-5-1, and 2-10-1. The neural network diagrams for these three networks are shown in Fig. 4.

3 Result and Discussions

The result of ANN simulation for the hardness of weld nugget with FSW parameters rotation rate and welding speed is shown in Fig. 5. Three networks 2-1-1, 2-5-1, and 2-10-1 are applied for simulation. The increase in hidden layer neurons improves the coefficient of correlation. The correlation coefficient of networks 2-1-1, 2-5-1, and 2-10-1 are 0.96,415, 0.96,198, and 0.97,831, respectively. The predicted hardness

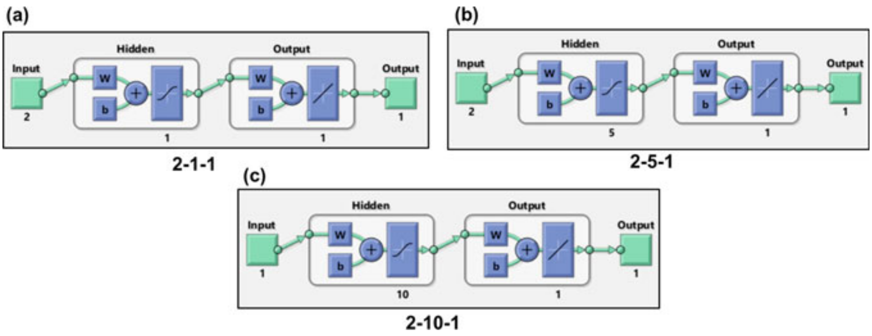


Fig. 4 Neural network diagrams for **a** 2-1-1 network, **b** 2-5-1 network, and **c** 2-10-1 network

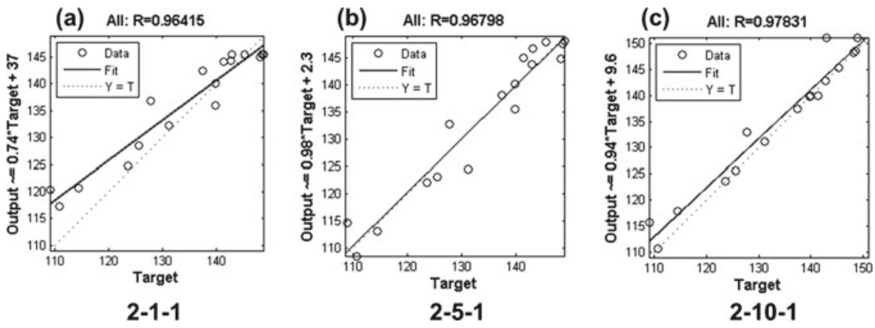


Fig. 5 The correlation between output and target value of hardness for weld nugget for networks: **a** 2-1-1, **b** 2-5-1, and **c** 2-10-1

value of weld nugget (output) showed a better correlation with the target values or literature values. The 2-10-1 network exhibited the best correlation.

The result of ANN simulation for the hardness of the HAZ with FSW parameters rotation rate and welding speed is shown in Fig. 6. The correlation coefficient of 2-1-1 and 2-5-1 networks are 0.95576 and 0.95361, respectively. There is no significant change in the correlation coefficient among 2-1-1 and 2-5-1 networks. Whereas a further increase in hidden layers neuron in 2-10-1 improves the coefficient of correlation to 0.96494. Thus, it is confirmed that the increase in hidden layer neurons improves the coefficient of correlation in general.

The result of ANN simulation for a peak temperature of weld nugget with FSW parameters rotation rate and welding speed is shown in Fig. 7. Here, three networks 2-1-1, 2-5-1, and 2-10-1 are applied for simulation, which showed the trend of improvement of the coefficient of correlation with the increase in hidden layer neurons. The correlation coefficient of networks 2-1-1, 2-5-1, and 2-10-1 are 0.8,531, 0.94,734, and 0.96,089, respectively. The predicted peak temperatures value of weld nugget (output) showed a better correlation with the target values. The 2-10-1 network exhibited the best correlation in comparison to 2-1-1 and 2-5-1 network.

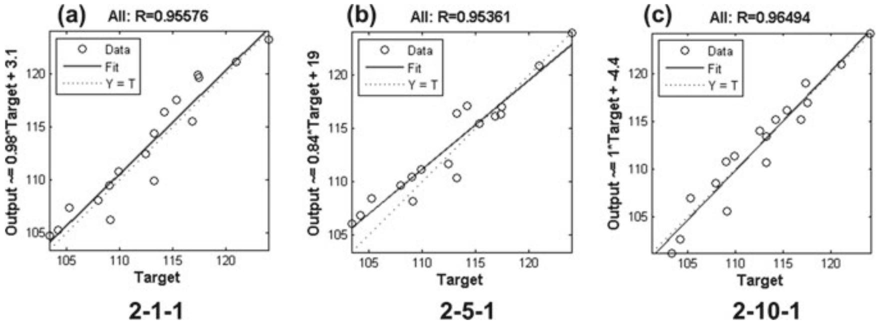


Fig. 6 Correlation between output and the target value of hardness for the HAZ for networks: **a** 2-1-1, **b** 2-5-1, and **c** 2-10-1

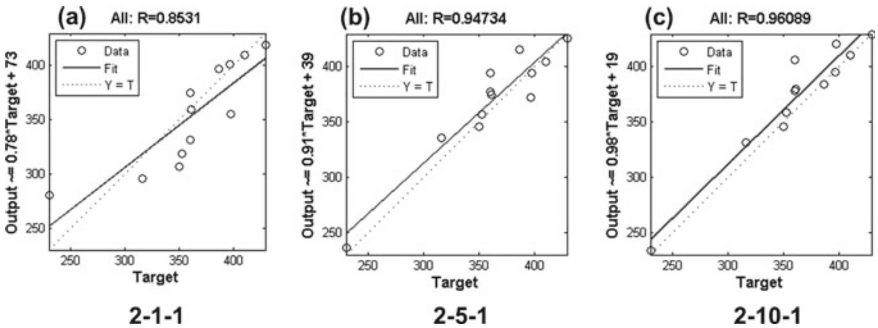


Fig. 7 Correlation between output and target value of peak temperature for weld nugget for networks: (a) 2-1-1, (b) 2-5-1, and (iii) 2-10-1

The result of ANN simulation for a peak temperature of HAZ with FSW parameters rotation rate and welding speed are shown in Fig. 8. The correlation coefficient of 2-1-1, 2-5-,1 and 2-10-1 networks are 0.8,531,0.94,734, and 0.96,089, respectively. The increase in hidden layer neurons improved the correlation coefficient significantly. The output values showed a better correlation with the target values and it is confirmed that the correlation improves with increase in hidden layer neurons.

The above ANNs results confirmed that an increase in hidden layer neurons improves the correlation coefficient for both hardness and peak temperature simulations. In the present study, ANN also performed for peak temperature apart from mechanical property hardness. 7050 alloy is precipitation strengthened alloy and strongly depend on the thermal cycle. The FSW process generates significant strain and enormous heat. The high strain produced during the FSW process reduces the grain size, which increases the strength. Although, the main strengthening mechanism in 7050 is precipitation strengthening. As discussed earlier, the η' phase is strengthening phase and the formation and dissolution depend on the thermal cycle, mainly, peak temperature. Another phase η which has less contribution to

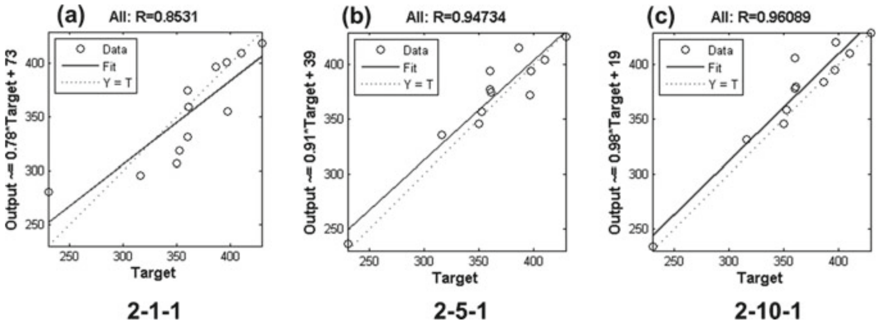


Fig. 8 Correlation between output and the target value of peak temperature for HAZ for networks: **a** 2-1-1, **b** 2-5-1, and **c** 2-10-1

the strengthening of alloy compared to η' phase starts coarsening above 250 °C and dissolve above 320 °C [4, 12–14]. The peak temperature observed during FSW process is significantly higher than 190 °C, dissolving temperature of strengthening η' phase [4, 12–14]. Thus, η' phase dissolved during the heating cycle. The FSW parameters which exhibited the highest peak temperature re-dissolved the η phase and subsequent cooling generates GP zones and thus has higher hardness than lower peak temperature. This confirms the higher hardness of alloy with increasing peak temperature.

4 Conclusions

The conclusions are:

1. ANNs are developed for the FSW process of AA7050 alloys.
2. The output parameters such as hardness of nugget of weld zone, the hardness of the HAZ, the peak temperature of nugget of weld zone, and HAZ showed a better correlation coefficient.
3. The correlation coefficient is improving with an increase in neurons in hidden layers. The neural network 2-10-1 showed a better correlation in comparison to 2-1-1 and 2-5-1.

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