Wear parametric Optimization of FSW parameters on Al Alloy Using MLP technique

N. Rao Cheepurupalli[1*], *Sathish* Selvaraj[2], *Srinivas* Reddy Muthadi[3], *LSP*. Subbu[4], *Lade* Jayahari[5], *Mohammed* H. Fallah[6],

[1]Department of Mineral Processing and metallurgical engineering, Faculty of Mines, Aksum University, Ethiopia.
[2]Department of Mechanical Engineering, Sri Ramakrishna Engineering College, Coimbatore, Tamilnadu, India
[3]Department of Mechanical Engineering, CVR College of Engineering, Hyderabad, Telangana, India
[4]Mechanical Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Telangana, India.
[5]Department of Mechanical, KG Reddy College of Engineering & Technology, Hyderabad, Telangana, India.
[6]Department of Refrigeration and air Conditioning Techniques engineering, College of technical engineering, The Islamic University, Najaf, Iraq.

Abstract. The purpose of this study was to identify the suitable Friction Stir Welding (FSW) parameters that would be used for welding scrapped Al alloy plates. On the experimental side, the study used four Factor Three-Level Full Factorial Design of Experiments (DoE) approach. Some of the input parameters incorporated in the analysis were the applied load, the sliding speed, displacement and weight percentage of Al2O3 reinforcement, and some of the output parameters were the specific wear rate and the coefficient of friction. The above said optimum parameters were established using the Minitab software while the above said experimental results was estimated using multilayer perceptron of the feed forward 4–10–1 network. For the actual test data set in the given experiment, the overall performance of the MLP predictions resulted to an R^2. This results to a coefficient of determination (R R^2 of 0.98474 and a mean squared error (MSE) of 0. 025075. Therefore the high R values, which are near to 1, show that the actual values mean and the predicted values mean are closely matched.

Keywords: Al plate, FSW, DOE, multilayer perceptron and specific wear rate

1 Introduction

FSW is an excellent example of engineering advancement that improves through ML and ANN. These technologies are changing the approaches to modelling and managing the

[*] Corresponding Author - nraocheepurupalli@gmail.com

FSW process in accordance with the general tendencies in industrial development aimed at the increase of productivity and the reliability of weld joints[1,2] .

This technique has significant advantages over any of the other Welding methods since it is capable of joining parts which have a high difference in melting point as the operating temperature of the FSW technique is much lower compared to the base material's melting point. [3-5] .The possibilities that it has are numerous and these are: reduction of cost, increase of fatigue and tensile strengths, non-consumable tool, low impact on the environment with regards to sustainability. Therefore, its application has immensely promoted the car manufacturing industry [6].

Several research articles of the last years focus on the advantages of ML and ANN for enhancing operations in FSW. Prabhakar et al. [7] provides a comprehensive investigation on the effect of FSW process parameters, which include the spindle speed, tool tilt angle, welding speed, and geometry of the tool shoulder on welding quality. They state their work and findings in relation to the use of integrated sensors to gather data together with AI algorithms for analysis with a significant enhancement in weld quality. Through quantitative analysis and qualitative validation of optimization, this research establishes that ML is indispensable in explaining the subtleties of welding parameters to produce efficient joints amidst the advances in modern FSW processes[8-11].

Our task is to study the wear characteristics such as the paricular wear rate, and coefficient of friction for the friction stir welded scrapped al alloy. The results of both the outputs, SWR and (COF), are predicted with the help of the multilayer perceptron (MLP) network [12-15].

2 Experimentation procedure

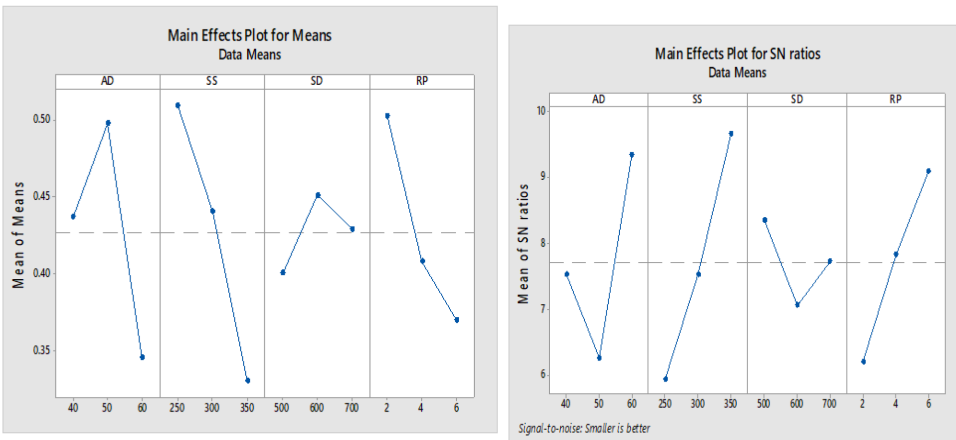
Table 1. Wear factors and levels

Factors	Symbols	Unit	Levels		
			1	2	3
Applied load	AD	N	40	50	60
Sliding Speed	SS	Rpm	250	300	350
Sliding Distance	SD	m	500	600	700
Reinforcement percentage	RP	%	2	4	6

Table 2. Wear characteristics results

S.No	AD	SS	SD	RP	Specific Wear Rate $*10^{-4}$ mm^3/Nm SWR	Coefficient of Friction (COF)
1	40	250	500	2	0.569	0.018
2	40	300	600	4	0.456	0.019
3	40	350	700	6	0.286	0.024
4	50	250	600	6	0.548	0.031
5	50	300	700	2	0.589	0.041
6	50	350	500	4	0.356	0.026
7	60	250	700	4	0.412	0.042
8	60	300	500	6	0.276	0.032
9	60	350	600	2	0.349	0.035

The aluminum (Al) samples are positioned on the POD apparatus in accordance with the DOE orthogonal array (L9), where material abrasion occurs between the disc and the samples. Throughout the process, the weight before and after experiments must be measured [16-19]. For optimizing wear behavior analysis, four factors—Applied load, Sliding Speed, Sliding Distance, and Reinforcement percentage—have been chosen at three different levels, as detailed in Table 1. The wear characteristics, including specific wear rate and coefficient of friction results, are presented in Table 2.

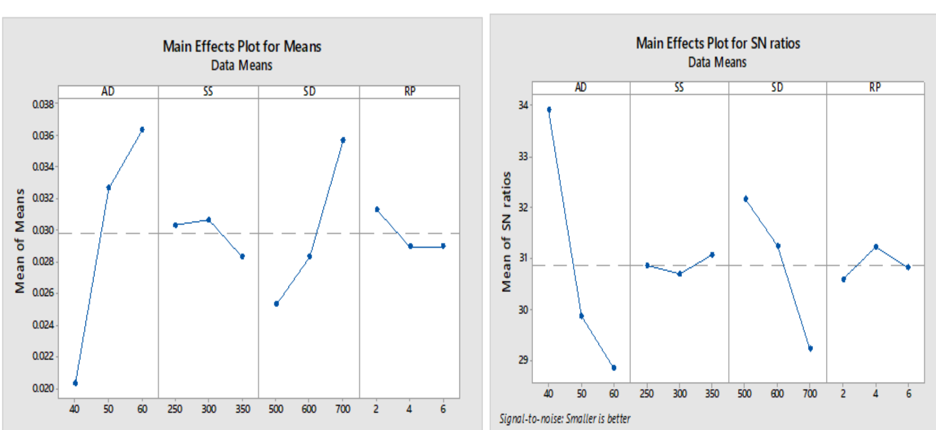


(a) (b)

Fig. 1 a&b. Mean and SN ratio plot for SWR

Table.3 SN ratio -SWR

Level	AD	SS	SD	RP
1	7.530	5.941	8.350	6.213
2	6.264	7.533	7.063	7.831
3	9.342	9.662	7.724	9.093
Delta	3.078	3.721	1.287	2.880
Rank	2	1	4	3



(a) (b)

Fig. 2a&b. Mean and SN ratio plot for COF

3 Result and discussion

The design of experiments was conducted using Minitab 18 software, incorporating various input factors for optimization [20-24]. The resulting mean and SN ratio for the SWR are presented in Figure 1 and Table 3. The optimal wear rate was achieved with the parameters AD2-SS1-SD2-RP1, corresponding to 50N, 250 RPM, 600m, and 2 wt% respectively. Similarly, the mean and SN ratio [25-29] for the COF are shown in Figure 2 and Table 4. The optimal coefficient of friction was obtained with the parameters AD3-SS2-SD3-RP1, corresponding to 60N, 300 RPM, 700m, and 2 wt% respectively. As indicated in Table 3, sliding speed is the most influential factor affecting the specific wear rate of aluminium plates. Table 4 shows that the applied load is the most significant factor influencing the coefficient of friction of aluminium plates[30-33].

Table 4. SN ratio -COF

Level	AD	SS	SD	RP
1	33.91	30.87	32.16	30.59
2	29.87	30.69	31.24	31.22
3	28.85	31.07	29.23	30.82
Delta	5.05	0.38	2.94	0.63
Rank	1	4	2	3

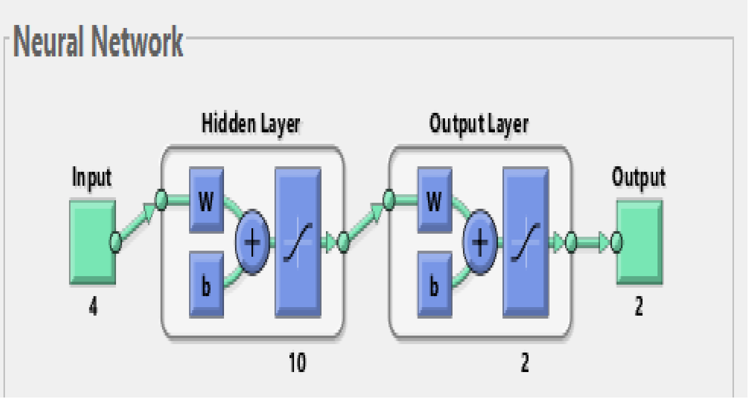


Fig. 3. MLP network

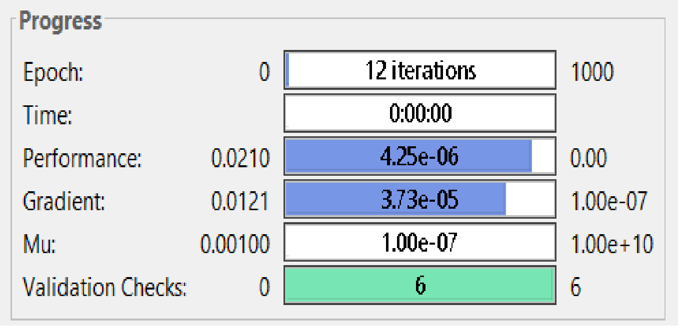


Fig. 4. Progress of MLP in matlab

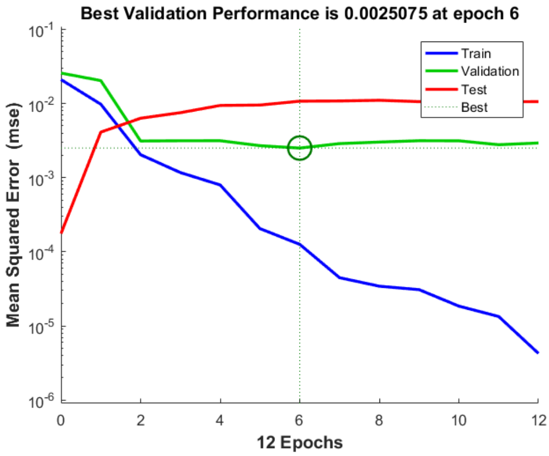


Fig. 5. Best validation performance for MSE

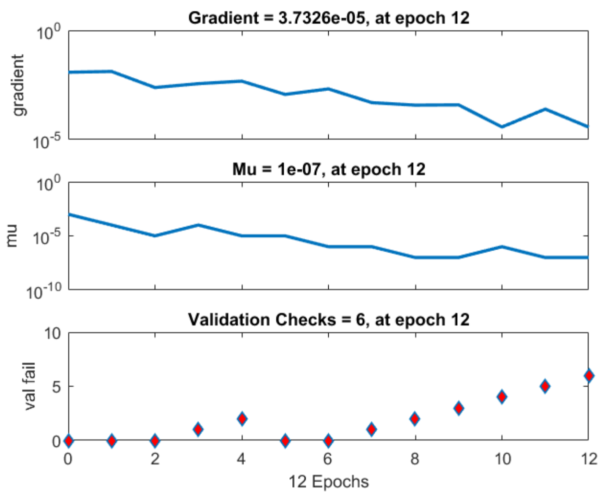


Fig. 6. Validation Check Diagram

In the present investigation, the wear behaviour of Al based composites was modelled and predicted using MATLAB R2019a. The inputs-output combination experimental values constituted the base upon which the network was trained. This dataset was divided into two modes: An input matrix and output matrix. The input parameters were the Applied load, sliding speed, sliding distance and reinforcement percentage while the output parameter measured was the Specific wear rate and Coefficient of friction [34-37]. Several networks were developed by performing experimentation with the training algorithms, the number of neuron layers, and the transfer functions of the hidden and the output layer to determine the best of all [10]. The choice in the training algorithm was the Levenberg-Marquardt algorithm since that is the fastest backpropagation algorithm and needs less memory space compared to other algorithms [10,21]. In MATLAB R2019a, error objectives were set at gradient as 0.0000372 and Mu at 1e-07 (Figure.5) . The optimal ANN model is 4–10–2 network configuration (Figure.3).The progress of MLP is shown in Figure.4.Regression analysis was conducted to evaluate the relationship between the ANN outputs and the corresponding targets [22,23]. The ideal 4–10–2 architecture is demonstrated by the comprehensive regression graph, which plots the network outputs against the targets.To predict wear characteristics , the optimal validation performance was achieved at epoch 6 with an MSE of 0.025075 (Figure.5 & 6), as shown by the MSE graph over 12 epochs for the three datasets . Generally, increasing the number of training epochs leads to a decrease in error [38-42]. However, once the network begins to overfit the training data, the error on the validation dataset can start to increase.

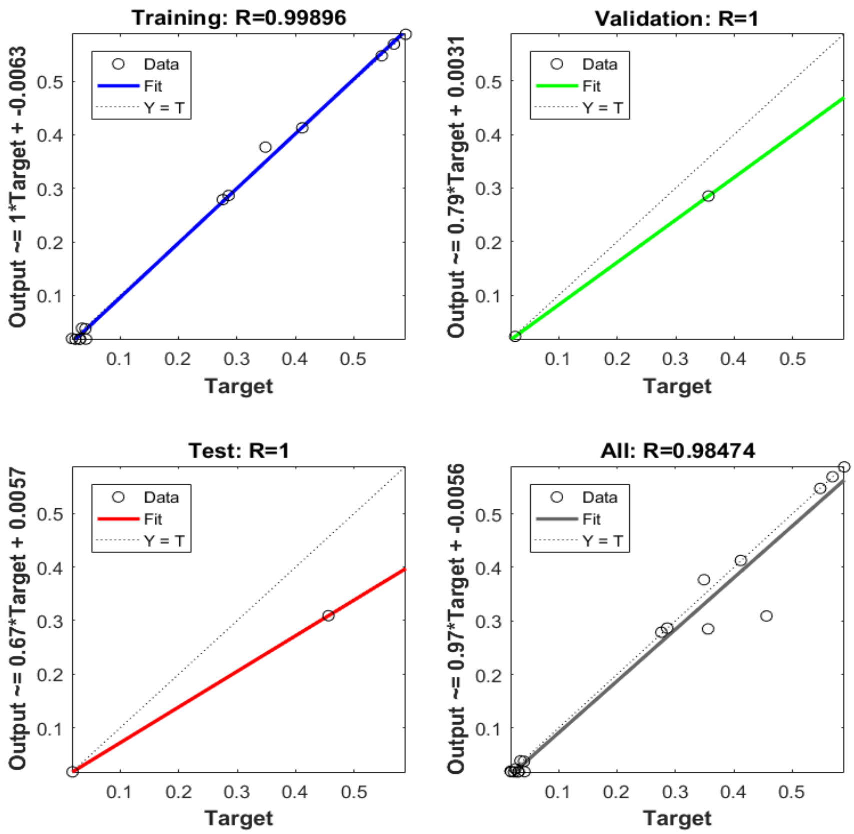


Fig. 7. Regression fit diagram

The corresponding correlation coefficients for three sets were 0.99896 ,1 and 1 respectively (Figure. 7). Thus, the correlation coefficient of all data combined, training, validation, and testing data is equal to 0. 98474. These correlation coefficients are very close to 1 and show that there is a high relation between the experimental values and the predicted values.

4 Conclusion

- Scrapped Al alloy plates are joined together with aid of friction stir welding. As per Minitab,L9 orthogonal array the experiments are conducted .
- The input variables included applied load, sliding speed, sliding distance, and Al2O3 reinforcement weight percentage, while the output variables were specific wear rate and coefficient of friction.
- From the result, The optimal wear rate was achieved with the parameters AD2-SS1-SD2-RP1, corresponding to 50N, 250 RPM, 600m, and 2 wt% respectively. The

optimal coefficient of friction was obtained with the parameters AD3-SS2-SD3-RP1, corresponding to 60N, 300 RPM, 700m, and 2 wt% respectively.

- For the given experimental dataset, the MLP predictions yielded an R^2 value of 0.98474 and MSE of 0.025075. These high correlation coefficients, close to 1

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