Artificial Neural Network Modeling for Predicting the Tensile Strength, Microhardness and Grain Size of Friction Stir Welded Dissimilar AA5083-AA6063 Aluminum Alloys Joints

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Abstract

Friction Stir Welding (FSW) has been established as one of the most promising processes for defects free joining of aluminum alloys. In present study artificial neural network (ANN) modeling for predicting the tensile strength, microhardness and average grain size at weld nugget zone of FS welded dissimilar AA5083-O/ AA6063-T6 aluminum alloys joint. Experiments are performed according to L_{27} OA which is decided based on process parameters and their levels. The developed ANN based model for tensile strength, microhardness and grain size has been found satisfactory with average percentage prediction errors of 1.094%, 1.078 and 1.583%, respectively. Analysis of Variance (ANOVA) is also used to find out the percentage contribution and significance of process parameters for quality characteristics. Based on ANOVA results, tool rotational speed is the significant parameter for tensile strength whereas welding speed is significant parameter for grain size.

Keywords: **Friction stir welding, aluminum alloys, artificial neural network, tensile strength, grain size.**

Introduction

Joining of aluminum alloys using conventional fusion welding processes results in various defects which include distortion, hot cracking, porosity, voids and lack of penetration in the joint.[1] Friction Stir Welding (FSW) which is a solid state technique is highly recommended to resolve these problems.[2] The principal of FSW process is very simple, in which a non- consumable rotating tool which consist of two parts namely a shoulder and a pin is inserted into the joint line of plates that to be joined. Due to the friction between the shoulder and work- piece surface, frictional heat is generated that plasticize the material around the pin. The combination of tool rotation and translation moved deformed material from front to back of pin producing the joint in solid state.[3]

For understanding the behavior of any manufacturing process modeling is the scientific way to quantitatively study the process behavior. In general, modeling of any process required large number of experimental results which has been found time consuming and costly. To overcome these problems artificial intelligence based artificial neural network (ANN) tool is used for modeling. The use of ANN as a modeling tool for predicting the properties of welded joints in FSW process is reported by very few researchers.[4-7] Lakshminarayanan et al. used response surface methodology (RSM) and ANN for prediction the tensile strength (TS) of FS welded AA7039 aluminum alloys. The results of the ANN model showed that it was more accurate for predicting the TS as compared with the RSM modeling.[4] Jayaraman et al. used RSM and ANN for predicting the tensile strength of FS welded A319 cast aluminum alloy. Authors found that the error rate predicted by ANN modeling was smaller as compared to RSM modeling.[5] Okuyucu developed ANN model for between the FSW parameters and mechanical properties. Authors found that developed ANN model can be used to obtain the mechanical properties of welded joints as a function of TRS and welding speed (WS). Predicted results using ANN model were in good agreement with measured results.[6] Shojaeefard et al. developed an ANN model the FSW parameters and mechanical properties of AA7075/ AA5083 butt joint. Authors observed the model was considered for predicting the ultimate tensile

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strength and hardness as functions of WS and TRS.[7] From available literature related to ANN modeling in FSW process, when compared the predicted results of RSM and ANN based model, the ANN based model predicted the more accurate results.

Al alloy	Si	Fe	Cu	Mn	Mg	Ti	Cr	Zn	Al
6063	0.420	0.160	0.001	0.001	0.53	0.013	0.00	0.00	98.875
5083	0.190	0.230	0.02	0.6	4.53	0.030	0.08	0.15	94.350

Table 1.Chemical composition of Al alloys

Al alloy	Ultimate Tensile strength (MPa)	Yield strength (MPa)	% elongation
AA6063	220	185	12.6
AA5083	290	181	24.4

Table 2.Mechanical properties of Al alloys

It is evident that very few works are reported in the area of ANN based modeling of FSW process parameters. The objective of present article is ANN modeling for prediction the tensile strength, microhardness and grain size of FS welded joint of dissimilar AA5083-O and AA6063-T6 aluminum alloys. TRS, WS, shoulder diameter and pin diameter have been selected as FSW process parameters.

Parameters	Symbol	Unit	Level 1	Level 2	Level 3
Tool rotational speed	N	RPM	700	900	1100
Welding speed	S	mm/min	40	60	80
Shoulder diameter	D	mm	15	18	21
Pin diameter	d	mm	4.5	5	5.5

Table 3.Process parameters and their level

Experimental Procedure

In this study, 6 mm thick sheets of dissimilar aluminum alloys AA 5083-O and AA 6063-T6 is used for welding. Chemical composition and mechanical properties of these aluminum alloys are given in table 1 and table 2, respectively. Four process parameters namely as tool rotational speed, welding speed, shoulder diameter and pin diameter with three levels were considered for welding as given in table 3.The dissimilar butt welding using modified vertical milling machine (make: BFW India) according to designed L_{27}OA matrix as given in table 4.

Exp. no.	Parameters				Tensile strength	Microhardness	Grain size
	N	S	D	d	TS (MPa)	MH (Hv)	GS (μm)
1	1	1	1	1	136.2	59.53	19.886
2	1	1	2	2	146.3	69.84	15.625
3	1	1	3	3	141.1	64.03	16.203
4	1	2	1	2	145	66.74	16.509
5	1	2	2	3	150.2	73.4	10.937
6	1	2	3	1	143.7	65.88	16.826
7	1	3	1	3	135.1	54.14	19.021
8	1	3	2	1	138.8	62.09	18.657
9	1	3	3	2	139.6	62.53	18.121
10	2	1	1	2	148.8	69.23	14.583

11	2	1	2	3	153.5	76.41	11.82
12	2	1	3	1	152.6	68.77	14.112
13	2	2	1	3	150.9	75.54	11.217
14	2	2	2	1	161.2	85.25	8.578
15	2	2	3	2	156.1	78.56	9.943
16	2	3	1	1	146.3	62.71	18.229
17	2	3	2	2	151.3	72.87	12.323
18	2	3	3	3	145.2	65.14	18.229
19	3	1	1	3	145.4	69.92	13.257
20	3	1	2	1	151.2	73.22	12.86
21	3	1	3	2	143.9	72.43	12.152
22	3	2	1	1	150.1	71.21	13.67
23	3	2	2	2	157.5	79.39	9.72
24	3	2	3	3	152.5	76.36	11.513
25	3	3	1	2	137.5	66.54	17.156
26	3	3	2	3	147.5	72.15	12.152
27	3	3	3	1	142.5	62.45	17.5

Table 4.Experimental layout according to L_{27} OA and responses

The quality characteristics or responses selected are tensile strength (TS), microhardness at weld nugget zone (MH) and average grain size (GS) at weld nugget zone of welded joint. Tensile test specimens of welded joints were prepared according to ASTM-E8 standard using wire EDM along the transverse direction of weld joint line.[8] Tensile tests were performed using universal testing machine (make: Bangalore Integrated System Solutions (P) Ltd. India) having a load capacity of 25 kN. The average of three tests was considered as tensile strength. The tensile test specimens before the test and after the test are shown in fig. 1. The hardness at weld nugget zone of the joints is measured using Vickers microhardness (make: Omni TECH India) tester with 20gm load at 20 second dwell time. For measuring GS at weld nugget zone specimens are cut along the transverse direction of the joint line from the welded plates. The microstructure specimens are prepared according to standard procedure and modified kellers reagent (75 ml H_2O, 3ml HF, 3 ml HCl and 1.5 ml HNO_3) is used for etching. The microstructure analysis is carried out using an optical microscope (Model: LEICA DM 2500 M). The experimental results of TS, MH and GS are presented in table 4.

Figure 1.Tensile test specimens before and after test

ANN Modeling

ANN is information processing architecture in which a large number of highly interconnected neurons are working together. On the basis of number of hidden layers and number of neurons in hidden layers the architectures of the network has been decided before training a network. For selecting the number of neurons in hidden layer, mean square error (MSE) has been calculated for different number of neurons and on the basis of minimum MSE number of neurons have been selected in hidden layers.

The experimental results of different responses have been normalized by using following equation:

$$y_{ij}^{*} = \frac{y_{ij}}{\max \ y_{ij}} \qquad (1)$$

where y_{ij}^{*} is the normalized value of the j^{th} responses in i^{th} experiment, y_{ij} is the actual value of j^{th} responses in i^{th} experiment and max y_{ij} is the maximum value y_{ij}.

In this study normalized experimental data of TS, MH and GS have been used for training the network. The network contains three layers, first hidden layer with four neurons corresponding to the four inputs, second layer as hidden layer with eight neurons and third layer with three neurons corresponding to three outputs. Therefore, a network of 4-8-3 structure was found to be the suitable network for present study Neural Network Toolbox commercially available software package neural network toolbox of MATLAB is used for training the network for minimization MSE of the network.

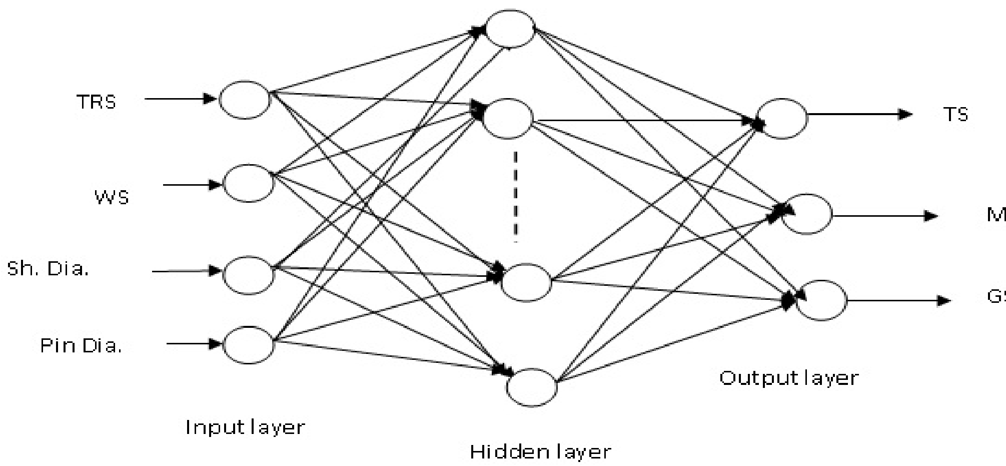

Figure 2.Three layer architecture used for ANN modeling

Results and Discussion

Model Validation

Theoretical Validation: The regression analysis has been carried out for verify the developed ANN model predicted data is well fitted or not. The regression coefficients for training, testing and validation have been found as 0.99932, 0.99275 and 0.99275, respectively. The overall regression coefficient has been found as 0.99356. These coefficients are in acceptable range (very close to 1), hence the data predicted for different quality characteristics using developed ANN model are well fitted.

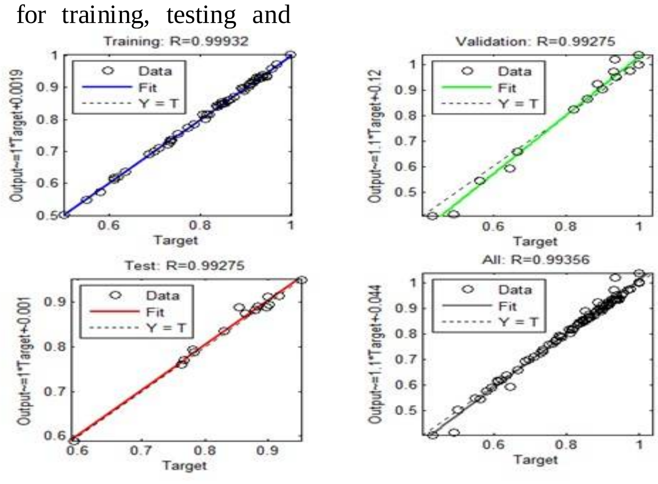

Figure 3.Regression plots for ANN model

Exp. No.	Experimental results (normalized from Eq. 1)			ANN predicted			Pre. Percentage error		
	TS	MH	GS	TS	MH	GS	TS	MH	GS
1	0.85	0.6983	1	0.84491	0.67826	1.0659	0.509	2.004	6.59
2	0.90407	0.81924	0.78573	0.90757	0.81564	0.78277	0.35	0.36	0.296
3	0.87762	0.75109	0.81479	0.87531	0.7709	0.84946	0.231	1.981	3.467
4	0.91141	0.78287	0.83018	0.8995	0.78757	0.83524	1.191	0.47	0.506
5	0.91152	0.861	0.54998	0.93176	0.85356	0.63689	2.024	0.744	8.691
6	0.88779	0.77279	0.84612	0.89144	0.76897	0.84328	0.365	0.382	0.284
7	0.84499	0.63507	0.9565	0.83809	0.63792	0.96654	0.69	0.285	1.004
8	0.86682	0.72833	0.9382	0.86104	0.72064	0.93943	0.578	0.769	0.123
9	0.8633	0.73349	0.91124	0.866	0.73972	0.91273	0.27	0.623	0.149
10	0.94345	0.81208	0.73333	0.92308	0.82623	0.71008	2.037	1.415	2.325
11	0.94922	0.8963	0.59439	0.95223	0.88839	0.58987	0.301	0.791	0.452
12	0.9382	0.80669	0.70964	0.94665	0.82156	0.71502	0.845	1.487	0.538
13	0.96722	0.8861	0.56407	0.9361	0.89542	0.55125	3.112	0.932	1.282
14	1.0081	1	0.43136	1	1.0013	0.43348	0.81	0.13	0.212
15	0.96262	0.92152	0.5	0.96836	0.93481	0.51796	0.574	1.329	1.796
16	0.88827	0.7356	0.91668	0.90757	0.72933	0.90653	1.93	0.627	1.015
17	0.94796	0.85478	0.61968	0.93859	0.88145	0.63547	0.937	2.667	1.579
18	0.89472	0.76411	0.91668	0.90074	0.75991	0.91308	0.602	0.42	0.36
19	0.90498	0.82018	0.66665	0.90199	0.8172	0.66264	0.299	0.298	0.401
20	0.93531	0.85889	0.64669	0.93797	0.84489	0.6404	0.266	1.4	0.629
21	0.91439	0.84962	0.61108	0.89268	0.85594	0.62234	2.171	0.632	1.126
22	0.91872	0.83531	0.68742	0.93114	0.84106	0.68759	1.242	0.575	0.017
23	0.96685	0.93126	0.48879	0.97705	0.96929	0.45463	1.02	3.803	3.416
24	0.93976	0.89572	0.57895	0.94603	0.89878	0.58022	0.627	0.306	0.127
25	0.88786	0.78053	0.86272	0.85298	0.79308	0.87509	3.488	1.255	1.237
26	0.94016	0.84633	0.61108	0.91501	0.87819	0.65913	2.515	3.186	4.805
27	0.88974	0.76774	0.88002	0.884	0.77049	0.88297	0.574	0.275	0.295
Average percentage prediction error							1.094	1.079	1.582

Table 5.Experimental results, ANN predicted results and predicted percentage error of normalized quality characteristics

Experimental Validation: The data predicted data of responses by ANN model has been compared with experimental results for different set of process parameters to check the validation of the ANN model. The comparative results for each response have been shown in table 5. Fig. 4 shows that the experimental results are closer with data predicted by ANN mode. The percentage of prediction error (PPE) has been computed using following equation.

$$PPE = \frac{|Experimental\ value - Predicted\ value|}{Experimental\ value} * 100 \qquad (2)$$

The maximum error of ANN model for tensile strength, microhardness and grain size have been found as 3.48%, 3.80% and 8.69%., and the average prediction error have found as 1.09% and 1.58% for tensile strength and grain size respectively, which are negligibly small. Hence, for the prediction the data of each response at different set of process parameters the developed ANN model may be used successfully for.

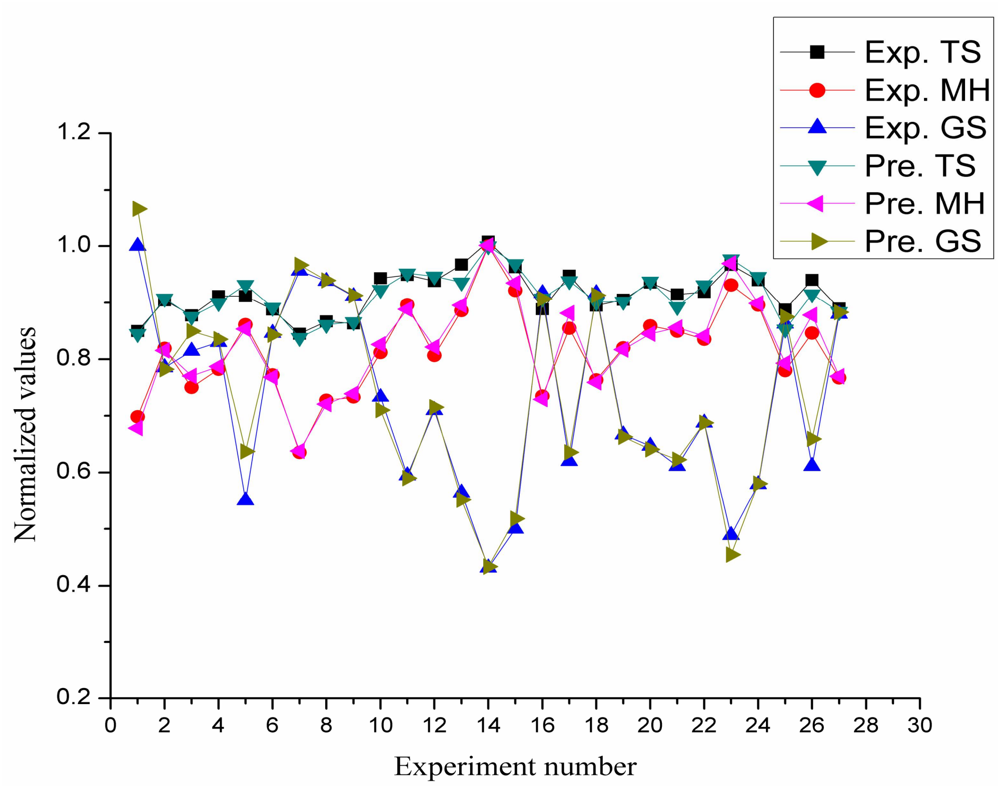

Figure 4.Experimental and predicted normalized values of quality characteristics

The significance and percentage contribution of process parameters for each objective is obtained by using ANOVA. The significance of each process parameter is found out in terms of F value and percentage contribution. The results of ANOVA are given in table 6. The result shows that tool rotational speed is more significant parameter for TS whereas welding speed is more significant parameter for MH and GS. The contribution of process parameters for tensile strength, and grain size is [N-42.52%, S-36.58%, D-20.78%, d-0.11%], [N-32.45%, S-40.10%, D-23.95%, d-3.50%] and [N-30.83%, S-40.01%, D-22.37%, d-6.79%] respectively.

Conclusions

From present study, application of ANN for predicting the TS and GS of FS welded joints of dissimilar aluminum alloys following conclusions are derived:

- The developed artificial neural network based model for TS, MH and GS has been found satisfactory with average percentage prediction errors of 1.094%, 1.078% and 1.583%, respectively.
- The predicted values by ANN model of TS, MH and GS values have been found close to the experimental values.
- Based on ANOVA results TRS is the significant parameter for TS whereas WS is significant parameter for MH and GS.

Response	Source	DF	Seq SS	Adj MS	F-ratio	% of Contribution
TS	N	2	452.79	226.39	62.47	42.52
	S	2	389.55	194.77	53.74	36.58
	D	2	221.21	110.60	30.52	20.78
	d	2	1.27	0.63	0.17	0.11
	Error	18	65.24	3.62		
	Total	26	1130.04			
MH	N	2	378.80	189.40	52.46	32.45
	S	2	467.97	233.99	64.81	40.10
	D	2	279.35	139.68	38.69	23.95
	d	2	41.01	20.51	5.68	3.50
	Error	18	64.99	3.61		
	Total	26	1232.12			
GS	N	2	77.225	38.613	26.83	30.83
	S	2	100.238	50.119	34.82	40.01
	D	2	56.023	28.011	19.46	22.37
	d	2	17.016	8.508	5.91	6.79
	Error	18	25.907	1.439		
	Total	26	276.409			
Tabulated F-ratio at 95% and 99% confidence level: $F_{0.05,2,18} = 3.55$, $F_{0.01,2,18} = 2.62$ [9] # Insignificant						

Table 6.ANOVA results of TS, MH and GS

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