Application of an Artificial Neural Network Model to Predict Parameter of Friction Stir Spot Welding on Aluminum Sheet

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***Abstract* — This research was conducted to predict the maximum load in the Friction Stir Spot Welding process using Aluminum Alloy 1050 material. There are 4 variations of process parameters, namely tool pin diameter, tool rotation speed, welding speed which has 3 levels for each, and plunge depth which has 2 levels. The experimental design in this research used the Taguchi method with 54 experiments. The results of the Backpropagation Neural Network training have a 4-8-8-1 network architecture consisting of 4 input layers, 2 hidden layers with 8 neurons, and 1 neuron in the output layer. The activation function used is "logsig" and the training function is "trainrp". With this network architecture, the MSE is 0.00918 and the average error is 6.99%.**

***Keywords*—friction stir spot welding, maximum load, Taguchi, logsig, trainrp, backpropagation neural network.**

I. Introduction

Recently, because of its low weight, aluminum has become a structural energy-saving material considered in advanced Applications. In addition, aluminum can be recycled, it is an easily saved resource, and can also be expected to be an environmentally friendly metallic material. Friction Stir Welding (FSW) was originally developed by the United Kingdom Welding Institute (TWI) for aluminum alloys [1]. FSW is simply a solid-state joining method which is a mixture of extrusion and forging and not an actual welding process. Although the approach occurs below the melting point of the work piece material at a temperature, FSW has many benefits over fusion welding [3].

Friction Stir Spot Welding (FSSW) is a derivative of the Friction Stir Welding (FSW) method. The tool rotates and presses the material then the shoulder is exposed to the surface of the workpiece until the probe is inside the workpiece surface as shown in Fig. 1. In this position the workpiece is in a plastic condition due to heating caused by the touch of friction between the shoulder and the surface of the workpiece (the process of joining the material). The process is complete; the tool is lifted in the same loop. After lifting it will form a "hole" in the workpiece [2].

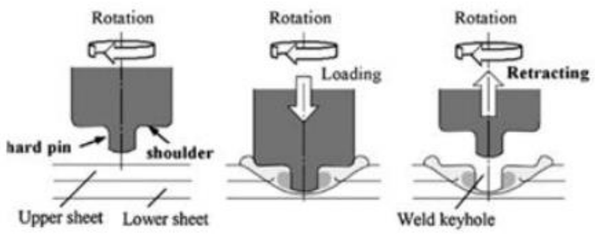


Fig. 1. Three stage of the FSSW process [2]

There are several studies related to the Artificial Intelligence (AI) applications, especially Artificial Neural Networks (ANN) for engineering areas such as prediction, tracking and control of manufacturing processes [3]. In image processing, ANN offers a lot very effective tools for image signal processing. Image pattern analyses, convolution neural network (CNN), and deep learning can be applied. Additional MATLAB has a function to connect microcontroller and camera device [4].

To find its input output relationships, conventional regression analysis was performed on some experimental data from a tungsten inert gas (TIG) welding process. By varying the input variables within their respective ranges, one thousand training data for ANNs were generated at random, and the responses were determined using the response equations obtained from the above traditional regression analysis for each combination of input variables [5].

In this research, the adaptation of the Artificial Neural Network to the welding of aluminum alloys was studied to create a connection between the aluminum sheet parameters of Friction Stir Spot Welding and the mechanical properties. The data was collected experimentally and then Artificial Neural Network was added.

II. RESEARCH METHODOLOGY

A. Research Design

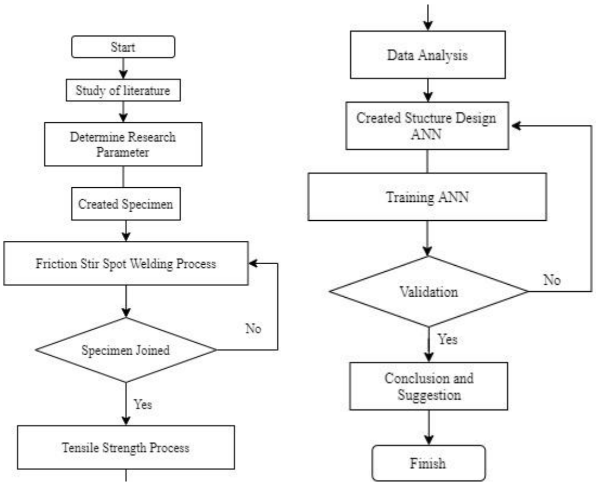


Fig. 2. Research design of FSSW experiment on AA1050

Fig. 2 shows the steps that will be carried out in the research. The first step is to prepare the test specimen which is then cut according to the standard size of the test. After the test is made, the friction stir welding process is carried out. After that, the mechanical properties were tested on the specimen test. After testing the mechanical properties, the resulting data were analyzed by Neural Network and finally conclusions were drawn.

B. Specimen

Welding specimens that will be used in this study is Aluminum A1050 with a thickness of 400 m. Based on the Japanese Industrial Standard (JIS) Z 3136:1999, the specimens in the form of Aluminum Alloy were cut to a size of 25 mm x 100 mm for each. The material that has been cut is then arranged in 25 mm overlap, as shown in Fig. 3.

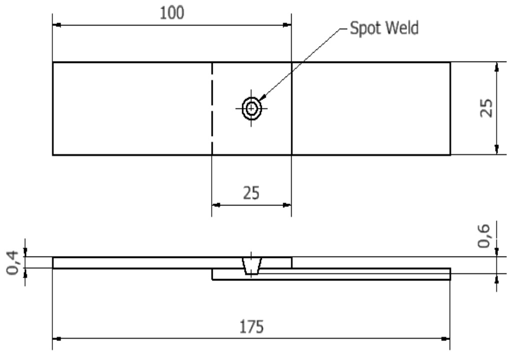
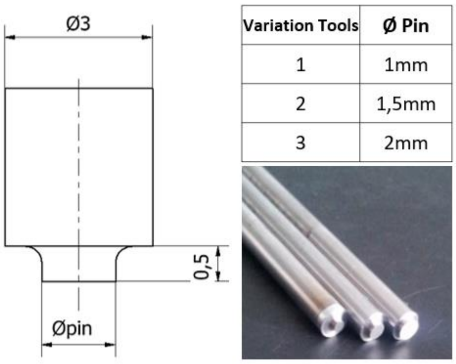


Fig. 3. Specimen test dimension

C. Geometry of Tool Diameter

The tool is a major part of the Friction Stir Spot Welding process. This study uses High Speed Steel (HSS) for the FSSW process tools. There are three tool designs made for this experiment with a tilt angle of 0° and the same shoulder size, the difference is the pin diameter. For more details see Fig. 4.



Variation Tools	Ø Pin
1	1mm
2	1,5mm
3	2mm

Fig. 4. Tool geometry and tool variation

D. Friction Stir Spot Welding Machine

The Friction Stir Spot Welding (FSSW) machine used to join the material type AA1050 is Milling Machine Makino KE55 as can be seen in Fig. 5. This machine is used to get variation on welding speed (12 mm/min, 18 mm/min, 24 mm/min) and variation on rotation speed (1500 rpm, 2000 rpm, 2500 rpm).

Fig. 5. Specification CNC milling machine

E. Tensile Test Machine

The tensile testing machine used in this research is Galdabini branded machine as can be seen in Fig. 6. The parameters used in this tensile test are : Load Cell : 2500N, Test speed : 5 mm/min, Sample Type : Rectangular, and Pre Tension : OFF.

Fig. 6. Tensile testing machine

F. Experiment Design

Taguchi method recommends that the orthogonal matrix to be used must have a degree of freedom greater than the total degrees of freedom of the process parameter [6]. In this research, the measurement of the number of parameter process and the number of levels was determined by the Degree of Freedom as shown in Table 1.

TABLE I
DEGREE OF FREEDOM PARAMETER AND LEVELS

No	Variable Parameter Process	Number of Level (k)	V_{fl} = (k- 1)
1	Tools Rotation Speed (rpm)	3	2
2	Welding Speed (mm/min)	3	2
3	Tools Pin Diameter (mm)	3	2
4	Tool Plunge Depth (µm)	2	1
	Total Degree of Freedom (V_{fl})		**7**

The orthogonal matrix from Taguchi method used is L_{27} (3^{13}). The L_{27} (3^{13}) orthogonal matrix consists of 27 experimental designs, 3 levels and 13 parameter processes. However, in this study only 4 variable of process parameter used according to the number of factors studied.

III. RESULTS AND DISCUSSIONS

A. Data Analysis

The experiment was carried out by combining variables of Friction Stir Spot Welding process parameter. Process Parameter used in this study are Tools Diameter, Tool Rotation Speed, Welding Speed with 3 variation of level, and Tool plunge depth with 2 variation of level. The four process parameters are assumed to have a significant effect on the maximum load response of the Aluminum Alloys (Table 2).

TABLE II
ALUMINUM ALLOY SPECIMEN TEST RESULT DATA

No Specimen	Process Parameters			Maximum Load (N)	
	Diameter Tools (mm)	Tools Rotation (rpm)	Welding Speed (mm/min)	(depth 500 µm)	(depth 600 µm)
1	1	1500	12	42.18	55.50
2	1	1500	18	38.03	50.70
3	1	1500	24	28.08	39.00
4	1	2000	12	47.68	56.11
5	1	2000	18	24.38	36.94
6	1	2000	24	12.14	24.20
7	1	2500	12	44.38	58.40
8	1	2500	18	35.84	30.70
9	1	2500	24	13.45	24.60
10	1.5	1500	12	51.17	73.10
11	1.5	1500	18	39.88	60.70
12	1.5	1500	24	15.38	40.40
13	1.5	2000	12	50.54	78.50
14	1.5	2000	18	38.91	51.88
15	1.5	2000	24	25.34	35.20
16	1.5	2500	12	53.90	84.20
17	1.5	2500	18	16.00	38.64
18	1.5	2500	24	40.14	28.60
19	2	1500	12	71.03	93.46
20	2	1500	18	70.39	77.58
21	2	1500	24	27.55	50.27
22	2	2000	12	79.56	101.66
23	2	2000	18	52.44	79.45
24	2	2000	24	37.94	61.20
25	2	2500	12	74.94	113.00
26	2	2500	18	54.41	83.34
27	2	2500	24	39.67	55.10

B. Backpropagation Neural Network Parameters

- Activation Functions.
  From the MATLAB software, there are 2 types of activation functions used in this study, namely the *tansig function* (sigmoid bipolar) which has a range (-1, 1), and the *logsig function* (binary sigmoid)

which has a range (0.1). From the two functions, determine which one has the smallest MSE value to get a prediction that is close to the experiment [7].

- Training Function
  The training function used to speed up the training process in the BPNN is *trainrp function* (Resilient Backpropagation). This function divides the direction and weight change into 2 different parts, so when using the drop method fast, only the direction is taken [7].

- Number of Neuron on Hidden Layer
  The number of neurons in each hidden layer is determined based on certain calculation methods, namely "n / 2", "1n", "2n", and "2n + 1", where "n" is the number of parameters of the research process (input layer) [7]. In this study the number of neurons in the hidden layer is limited to only 2 hidden layers. The number of neurons in each hidden layer is 2, 4, 8, and 9, and is limited to only using 4, 8 and 9 neurons.

- Learning Rate
  In this study, the learning rate used is 0.01 for all combinations of qualified parameters of the BPNN.

- Percentage of Training Data and Test Data
  Data training backpropagation consists of data training, test and validation. The comparison of the volume of data used in MATLAB software by default for preparation, testing and validation is 60 %: 20 %: 20 %. The comparison of training data and testing data in this study is 80%: 20%.

- Stopping Criteria (Table 3)

TABLE III
STOPPING CRITERIA

No.	Scrip	Value
1	net.trainParam.epochs	1000
2	net.trainParam.time	500
3	net.trainParam.goal	1e-2
4	net.trainParam.min_grad	1e-10
5	net.trainParam.max_fail	10

C. *Comparison between the experimental results and the predicted results of BPNN*

To determine the success rate of BPNN in predicting the observed response, the calculation of the difference (delta) between the experimental results and the predicted results of the BPNN target was carried out. The mean difference test was conducted to see if there was a significant difference between the actual test result response and the predicted response [8]. In addition, accuracy testing is also carried out by looking at the MSE value. The smaller the MSE value, the better the network architecture in predicting the target.

TABLE IV
BACKPROPAGATION PARAMETERS

No	Hidden Layer	Neuron	Activation	Training	Learning Rate
1	2	4	tansig	trainrp	0.01
2	2	4	logsig	trainrp	0.01
3	2	8	tansig	trainrp	0.01
4	2	8	logsig	trainrp	0.01
5	2	9	tansig	trainrp	0.01
6	2	9	logsig	trainrp	0.01

Table 4 shows the difference in the number of neurons and the activation function that will be used as parameters to get the most optimal network training results using MATLAB software.

TABLE V
BACKPROPAGATION PARAMETER TEST RESULTS

No	Experiment (N)	Training BPNN Result Data (N)					
		Tansig			Logsig		
		4 neurons	8 neurons	9 neurons	4 neurons	8 neurons	9 neurons
1	42.18	41.7217	63.8866	38.812	46.68	52.39	32.26
2	38.03	45.612	30.1295	39.4252	38.41	38.25	31.12
3	28.08	28.5386	21.6305	19.8864	10.35	27.98	30.25
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
52	113.00	102.32	98.3561	111.1914	110.79	112.9	117.08
53	83.34	81.9907	78.2033	80.9538	86.44	83.46	84.22
54	55.10	46.699	50.9058	77.2769	52.07	55.06	31.69
MSE		**0.00996**	**0.00926**	**0.00959**	**0.00999**	**0.00918**	**0.00993**
Epoch		**271**	**20**	**21**	**132**	**19**	**27**
Average Error		**17.80%**	**15.83%**	**12.41%**	**11.20%**	**6.99%**	**14.42%**

The results of the training test at BPNN (Due to limited writing space, the original data was 54 data, limited in number as shown in Table 5), it can be seen that there are several variations in the results of network training with different activation function parameters and different numbers of neurons. Activation of the logsig function with 8 neurons (yellow color) is the result that is closest to the response. This is indicated by the smallest MSE and Average Error values compared to other network training. From these MSE differences, it can be explained that the use of hidden layers can improve network performance created [9].

Determining the number of networks in the hidden layer is one of the most influential parameters in predicting, but there is no sure way to determine the number of hidden network neurons, to get the right composition it is usually done several times and the architecture that gives the best prediction results will be taken [10].

D. Network Form of BPNN

The results of training for the BPNN architectural network shown in Table 5 indicate that the lowest Mean Square Error (MSE) value is 0.00918 and lowest average error is 6.99%. A variation of 4-8-8-1 architectural networks includes this architectural type. The 4-8-8-1 network design, as shown in Fig. 7 suggests that the network has 4 neurons in the input layer, two hidden layers of 8 neurons, and one neuron in the output layer and the detail of model BPNN model shown in Table 6.

TABLE VI
DETAIL OF NETWORK ARCHITECTURE MODEL

Input Layer	Hidden Layer	Neurons	Output layer
1. Diameter Tool **2.** Tool Rotation **3.** Welding Speed **4.** Plunge Depth	**2**	**8**	**1.** Maximum Load

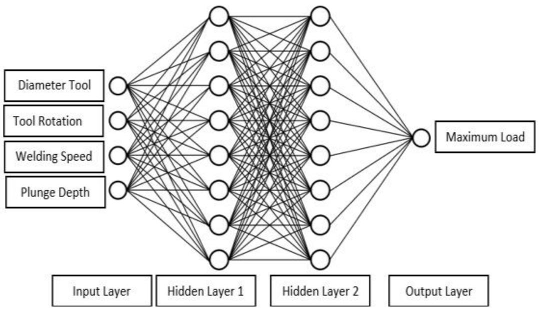


Fig. 7. BPNN network architecture

IV. CONCLUSIONS AND RECCOMENDATIONS

A. Conclusions

From experimental data with variations in the FSSW process parameters, the response was obtained in the form of maximum load (N), then it was modelled with various kinds of Artificial Neural Network that were able to predict independent variables and response. The most optimal ANN is a network with backpropagation type, with *logsig* activation function, and *trainrp* training algorithm. This network has an architecture of 4 input layers, 2 hidden layers with 8 neurons in each layer and 1 output layer. The MSE calculation results and the average error on the 4-8-8-1 network architecture produce a maximum load prediction that is closest to the target when compared to other architectural models, namely MSE of 0.00918 and an average error of 6.99%.

B. Recommendations

A suggestion for further research is to use other analytical methods that can find out how much influence each parameter of the Friction Stir Spot Welding process has. This can be used as an option for further research that has the desire to continue this research. In addition, it is highly recommended to use an optimization method that aims to find the value of each input parameter in order to get the maximum response. The level of precision of ANN is strongly supported by the large number of training data in the network, therefore the more data available, the more accurate it will be.

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