Feed-forward back-propagation (FFBP) algorithm for property prediction in friction stir spot welding of aluminium alloy

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Abstract. Facing the issue of cost and efficiency in experiments and tests in determining the properties of the welded structure is a challenge in friction stir spot welding (FSSW) optimization. Employing the machine learning technique of artificial neural network (ANNs) to develop a prediction model with fewer experiments and tests is a gentle solution to forecast the properties of the spot weld structures. In this study, the extended full factorial design with respect to the tool speed, plunge depth, and dwell time are applied to the FSSW specimens of aluminium A5052-H122 of 2mm thick through 27 experiments and evaluated via tensile shearing load testing. The multilayer neural network of feed-forward and back-propagation (FFBP) algorithm was engaged to learn and train the neural network iteratively with a set of weights and bias of 27 variations of inputs to fit the predicted tensile shear loads of the spot weld structures. Based on the resulted of regression plot, it is shown that the correlation coefficient (R) is perfect for training with the value of 0.999 and for testing the correlation coefficient (R) is reached to 0.958. However, the correlation coefficient is relatively good for validation with R equal to 0.921. For all data sets, the correlation coefficient is good with R of 0.833. It can be seen that the ANNs prediction model is relatively good since the correlation coefficient relatively close to 1.

Keyword: Friction stir spot welding, artificial neural network, aluminium alloy

1. Introduction
The issue in manufacturing demanding the process has to be quick and accurate in improving the quality of the manufacturing products. Friction stir spot welding (FSSW) as solid state welding process, has been broadly applied not only in manufacturing but also in many applications. FSSW is one of the welding technique used in Aluminium alloy as the variant of friction stir welding (FSW), developed by TWI in the UK in 1991 [1], offers advantageous more over low distortion and low energy consumption that normally used to replace resistance spot welding (RSM) due to weld consistency, short electrode tip life, and welding defect e.g. porosity or void [2]. Basically, FSSW is a complex process, affecting by factors of parameter such as spindle speed. The FSSW process generally
composed of three significant actions of plunging, stirring, and retracting as depicted in Figure 1. The plunging acts to move the FSSW tool reaches the workpiece until the tool pin plunged into the predetermined depth in the workpiece. When the shoulder reaches the top surface of the workpiece, friction is expanded and heat is generated significantly. The generated heat was formed due to friction among rotated tool and workpiece [2,3,4,5]. Furthermore, the stirring serves plastic deformation in the workpiece and allows the tool rotating at a certain time to form weldment [4]. Finally, the FSSW process is over through extracting the tool to the original position.

![Figure 1. The FSSW Process: (a) Plunging, (b) Stirring, and (c) Extraction [7].](image)

2. Problem Identification
Recent issue in manufacturing where such processes must be ran rapidly and properly to further improvement and performance of the welded structures, studies to optimize of FSW process has been done to define optimal settings of parameters. However, this technique competes with experiment cost as the price of raw materials and time-consuming. One heuristic approach is considered by employing machine learning technique to solve such issue that occurred many in manufacturing[6,7,8,9], and in welding [8,10]. An approach of machine learning technique such as Artificial Neural Networks (ANNs) can be found in [11,12,13,14].

3. Implementation of Artificial Neural Network
As a computational model, ANNs have been widely applied in engineering or manufacturing for optimization and forecasting. It is adopted brain system of human [15] consists of causality relation among factors yield outputs. This neural network is designed in such away able to determine outputs came from any alteration inputs accurately. The resulted output in this study is the mechanical properties of welded structure i.e. tensile strength influenced by input of governed parameters rotational speed and travel speed respectively. It is expected this machine learning technique is used instead of experimental work and test so that such of cost spent for experiment and tests can be eliminated and consequently reduce the time.

Basically the network can be described mathematically as a function of \( f \) about a distribution of \( x \) over \( y \) (\( f: x \rightarrow y \)). The networks could be composed of input, hidden, and output layer[16]. The network must be trained previously via function with trial and error of given ANN architecture and proposed algorithm to find the best solution. Training is complimented through multiplication and summation of weight and bias[17].

Figure 2 represents a basic structure of FF-BP neural network [18,19]. The tangent sigmoid (Tansig) (\( \text{Tansig}(x) \)) and linear \( \chi(x) \) are used as backpropagation function. The process of the neural network lay on the number of layers and neurons, where time is being an issue for such of complex structure of the network [16,17].
4. Experimental work
This study involved experimental work and mechanical testing. The extended full factorial design $3^3$ [21] was employed in the experimental work with respect to 3 factors at 3 levels. The 27 experiments of TSL-tests were performed to obtain 27 sets of input-output patterns for ANNs prediction model with 3 repetitions of each FSSW specimens to obtain the mean TSL which can be seen in Table 1. The FSSW specimen was made by using two pieces of 40×125 mm sheets with a 40×40 mm overlap area according to JIS Z3136:1999 standard [22], as depicted in Figure 3a. The type of FSSW tool was a flat shoulder with a cylindrical pin tool as depicted in Figure 3b made of VCN-150 steel that can withstand the high-temperature experience during the process with the chemical composition of AA5052-H112 and VCN-150 Steel are referenced in [23] and in [24] respectively.

![Figure 2. Basic Structure of Neural Network [18].](image)

![Figure 3. (a) Geometry of FSSW specimen AA5052-H112 in millimeters, (b) dimension of FSSW Tool.](image)
Table 1. TSL-tests Result from 27 Experiments as Output Response in ANNs Prediction Model.

| Test No. | Input Spindle speed (rpm) | Tool plunge depth (mm) | Dwell time (s) | Output Mean TSL (N) |
|----------|---------------------------|------------------------|----------------|-------------------|
| 1        | 1000                      | 2.5                    | 5              | 2923              |
| 2        | 1000                      | 2.5                    | 7              | 1772              |
| 3        | 1000                      | 2.5                    | 9              | 3369              |
| 4        | 1000                      | 3                      | 5              | 3179              |
| 5        | 1000                      | 3                      | 7              | 3900              |
| 6        | 1000                      | 3                      | 9              | 4255              |
| 7        | 1000                      | 3.5                    | 5              | 3179              |
| 8        | 1000                      | 3.5                    | 7              | 4313              |
| 9        | 1000                      | 3.5                    | 9              | 4255              |
| 10       | 1200                      | 2.5                    | 5              | 1988              |
| 11       | 1200                      | 2.5                    | 7              | 2018              |
| 12       | 1200                      | 2.5                    | 9              | 2334              |
| 13       | 1200                      | 3                      | 5              | 3852              |
| 14       | 1200                      | 3                      | 7              | 3287              |
| 15       | 1200                      | 3                      | 9              | 3699              |
| 16       | 1200                      | 3.5                    | 5              | 3846              |
| 17       | 1200                      | 3.5                    | 7              | 4165              |
| 18       | 1200                      | 3.5                    | 9              | 4387              |
| 19       | 1400                      | 2.5                    | 5              | 3846              |
| 20       | 1400                      | 2.5                    | 7              | 1901              |
| 21       | 1400                      | 2.5                    | 9              | 4387              |
| 22       | 1400                      | 3                      | 5              | 3365              |
| 23       | 1400                      | 3                      | 7              | 3121              |
| 24       | 1400                      | 3                      | 9              | 3125              |
| 25       | 1400                      | 3.5                    | 5              | 3980              |
| 26       | 1400                      | 3.5                    | 7              | 4100              |
| 27       | 1400                      | 3.5                    | 9              | 4650              |

5. Model Development

The topology of the ANN network model as depicted in Figure 4, was developed having one input layers consists of three neurons which corresponds to three inputs of main parameters i.e. spindle speed ($v$), tool plunge depth ($d$), and tool dwell time ($t$) [25]. Two hidden layer with each 15 and 7 neurons are set. A neuron was set in the output layer corresponds to output response of the tensile shear load (TSL). The data sets of 27 input-output patterns were then trained, tested and validated in Matlab environment. 70% of data was used for training, 15% for validation, and 15% for testing the model. The tensile shear load was considered as an output of neural networks. The conceptual structure for this proposed ANN is represented in the Figure 4.

In the network back propagation algorithm is involved which consists of two processes i.e. forward process and backward process. The forward process propagate input vector through the network to provide output at the output layer, and backward process propagates the error values back through the network to determine how the weights are to be changed during the training. The BP algorithm is used with a double hidden layer improved with training function called Trainlm with number of neurons of 15 for hidden layer-1 and 7 neurons for hidden layer-2.
6. Result and Discussion
In this session, the prediction model of the tensile shear load had been developed through ANN model. A detail result of 27 variation of TSL Test with 3 repetitions is tabulated in Table 1. Figure 5 represents the regression plot for all patterns in training, validation, and testing sets in the prediction model.

Figure 4. Topology of the Structure for a network in this study.

Figure 5. Regression Plot for all Patterns in Training, Validation, and Testing.
Based on the resulted plot, it is shown that the correlation coefficient (R) is perfect for training with the value of 0.999 and for testing the correlation coefficient (R) is reached to 0.958. However, the correlation coefficient is relatively good for validation with R equal to 0.921. For all data sets, the correlation coefficient is good with R of 0.833. It can be seen that the ANNs prediction model is relatively good since the correlation coefficient relatively close to 1.

7. Conclusion
The prediction system model for tensile shear load friction stir spot welding has been developed in this work. The proposed system model is develop in such away aimed to determine the desire information for the coming tensile shear load based on the selected parameters with reference the tensile shear load measurements. The extended full factorial design 3\(^3\)was employed in the experimental work with respect to 3 factors at 3 levels. The 27 experiments of TSL-tests were performed to obtain 27 sets of input-output patterns for ANNs prediction model with 3 repetitions of each FSSW specimens to obtain the mean TSL. The multilayer neural network of feed-forward and backpropagation algorithm which consists of one input layer, two hidden layers, and one output layer is used to learn and train the neural network iteratively with a set of weights and bias of 27 variations of inputs to fit the predicted tensile shear loads of friction stir spot weld. Based on the resulted of regression plot, it is shown that the correlation coefficient (R) is perfect for training with the value of 0.999 and for testing the correlation coefficient (R) is reached to 0.958. However, the correlation coefficient is relatively good for validation with R equal to 0.921. For all data sets, the correlation coefficient is good with R of 0.833. It can be seen that the ANNs prediction model is relatively good since the correlation coefficient relatively close to 1.

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