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Optimisation of Ultrasonically Welded Joints through Machine Learning

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Abstract

The quality of joint achievable through ultrasonic welding is highly dependent on the process input parameters. In this study an artificial neural network (ANN) is combined with a genetic algorithm (GA) to develop a high-fidelity model for predicting the strength of ultrasonically welded joints. Initial weights of the ANN were optimized using the GA. The model was then trained by the Levenberg-Marquardt algorithm on 27 training experiments and validated on 10 experiments. The model demonstrated a high level of accuracy with a mean relative error of 6.79% on validation data and a correlation coefficient of 0.9827 for all 37 experiments.

Keywords: Ultrasonic welding, Machine learning, artificial neural network, genetic algorithm, performance predictions

1. Introduction

Aluminium (Al) alloys are widely used in industry with applications ranging from electronic devices to aircraft structures. This is due to advantages such as high specific strength, corrosion/oxidation resistance and excellent processability [1]. Joining of aluminium structures is a key area of research with innovative technologies continuously emerging. Metal ultrasonic welding (MUSW) is one of the emerging technologies acquiring a lot of attention from both the research community and industry.

Ultrasonic welding (USW) uses ultrasonic energy at high frequencies (10-70 kHz) to produce high frequency, low amplitude mechanical vibrations (10-250 µm) [2]. MUSW uses high frequency mechanical vibrations to generate a friction-like shear relative motion between two surfaces. This results in local plastic deformation and shearing of the surface oxide layer, creating metal-to-metal contact area, resulting in a solid-state bond [1]. The extensive use of USW in industry is a result of its fast process times, low energy consumption, ease of automation and potential to become a smart manufacturing process[3].

The mechanical properties of the joint achieved through USW is highly dependent on the input process parameters. Various techniques are used to develop relationships, one such method is predictive modelling through artificial neural networks (ANN).

Machine learning is the ability of algorithms to extract useful models from raw data [4]. A commonly used machine learning architecture is the ANN, a computational structure inspired by a biological neural system, that has the ability to predict variables related to complex non-linear problems [5]. An ANN is composed of layers of neurons connected to each other by weights. Each neuron is characterised by its input, activation function and output. The first layer is defined the input layer, the last being the output layer and the remaining layers in-between are the hidden layers. Due to their high prediction potential, ANNs have been widely used in many real-world applications. For example, Ieracitano et al. [6] demonstrated ANNs prediction potential in accurately

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predicting (0.905 correlation coefficient between predicted and actual values) the diameters of polyvinylacetate nanofibers produced by an electrospinning process. Mondal et al. [7], also demonstrated ANNs prediction potential in accurately predicting (2.04 % maximum absolute error) the burr height produced by drilling aluminium.

Various researchers have developed ANN's to refine relationships between welding parameters and weld strength. Zhao et al. [8] developed an ANN model to predict the performance of MUSW joints, concentrating on clamping force, vibration time and vibration amplitude as the influencing parameters. The study highlighted the importance of multiple inputs and demonstrated that a high-fidelity predictive model of USW is achievable. The study in [8] concentrated on the time control USW mode, although the energy control mode is growing in popularity because of its ability to ensure the same amount of energy is absorbed at the weld interface for varying parts. Weld-by-time is an open-loop control system that ignores the fact that in real scenarios part dimensions vary and therefore, the time required for the weld interface to absorb the required energy varies. Following the work of Zhao et al. [8] and other researchers [9]–[11], Vangalapati et al. [11]applied an ANN to predict the joint performance for friction welding of aluminium alloy joints, demonstrating a high accuracy in predictions using the ANN. Li et al [9], applied an ANN to predict the joint performance in USW composite joints. The model inputs focused on material processing variables such as annealing temperature and surface condition, with the welding process parameters being energy, plunging speed and trigger force. This model demonstrated a high level of accuracy, however the model was not evaluated on validation data. Wang et al. [3] developed a finite element model (FEM) relating welding energy to weld lap shear strength. However, this model only accounts for one input parameter (weld energy). Venkatesan et al. [12] demonstrated the benefits of combing an ANN with a genetic algorithm (GA). The study focused on the optimisation of a machining process through a hybrid GA-ANN model. The study concluded that a GA-ANN model provides higher accuracy and requires less computational time promoting real time decision making.

In this paper, a GA is integrated with an ANN to develop a high-fidelity predictive model using energy, vibration amplitude and clamping force as process parameters. The model is trained on 27 experiments and validated on 10 experiments.

2. Experiments

The material used in this study is aluminium alloy (5754 – H111), cut into strips of dimensions 100 x 25 x 1 mm^3. Welding was conducted using a Branson Ultraweld L20 ultrasonic welders equipped with a 20 kHz power supply and a rectangular horn with dimensions of 18 x 10 mm^2. A schematic diagram of the ultrasonic welding configuration and the specimen dimensions can be seen in Figure 1. In this study the welding experiments were conducted using the energy control mode, which terminated automatically when the joint interface absorbed a preselected energy. Post-welding, the lap shear strength (LSS) of specimens was determined using a Tinius Olsen tensile tester equipped with a 10 kN load cell at a crosshead speed of 1.0 mm/min.

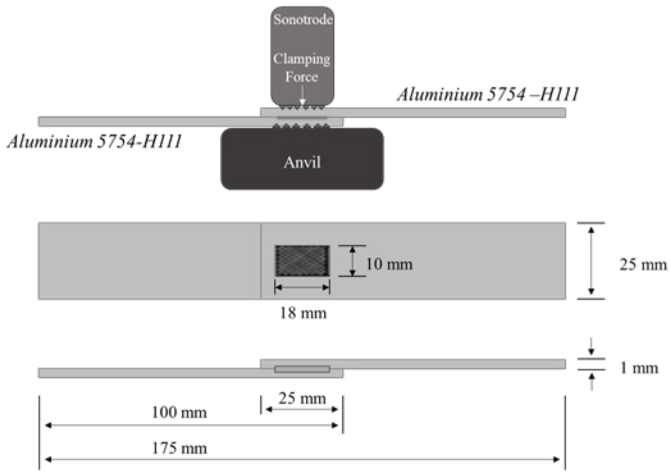

Figure 1 Schematic representation of the welding configuration and coupon dimensions

A design of experiments (DOE) was created to vary three input process parameters: energy, amplitude and clamping pressure. Various researchers such as Patel et al. [13] identified energy as being a key input parameter influencing joint strength, therefore energy was one variable element in the DOE. The amplitude correlates to the scrubbing action at the weld interface. Clamping pressure combined with this scrubbing action is what advances the weld. Hence, amplitude and clamping force were also selected as variable elements in the DOE.

A wide parameter range was selected for each of the variables, to provide data to characterise the welding process over a large application field. Preliminary testing discovered that USW of the test alloy requires the following: a minimum energy of 700 J to achieve a bond; 3 kJ produces a satisfactory joint; a clamp pressure exceeding 4.5 bar will result in no joint due to collapse and surface cracks. There is a single output variable, the lap shear strength (LSS).

Preliminary testing provided insight to aid the creation of the design of experiments (DOE). Table A-1 displays the DOE and the resulting LSS that was then used as training data for the predictive model. The model's performance was assessed on validation data as outlined in table 1. The validation data was predicted after each training iteration to assess the model's generalisation error and to prevent overfitting.

3. Artificial Neural Network Structure

Figure 2 is a schematic version of the architecture of the ANN used in this study. A key factor influencing the accuracy of the artificial neural network is the architecture design. Selecting the number of hidden layers and the number of neurons in each hidden layer is a challenging task as too few will result in underfitting and too many results in overfitting. In either scenario the model will perform poorly with a high generalisation error. The developer defines the number of layers and the number of neurons in each layer based on the structure of the training data. Related studies have demonstrated that two hidden layers is sufficient [8]. Therefore, in this study the ANN architecture consists of two hidden layers. The number of hidden neurons in each hidden layer was estimated by equation (1) [8]. The estimated configuration proved to be the most accurate in comparison to other architectures tested, such as a single hidden layer with 5-

10 hidden neurons and two hidden layers with 5-10 hidden neurons in each layer.

$$N_{hidden\ neurons} = 0.5(inputs + outputs) + \sqrt{number\ of\ training\ patterns} \quad (1)$$

There is a large unit difference between the input data, therefore data normalising was used to improve the accuracy of the training. Data normalising transforms the input data into a chosen range. In this study the data was normalised to values within the range of [0,1] and the function is as follows:

$$x_i = (x_i - x_{min})/(x_{max} - x_{\min}) \quad (2)$$

The node activation function is the main element of an ANN that enables the solving of complex nonlinear scenarios. In this study the transfer function is as follows:

$$f(x) = (1 + e^{-2x})^{-1} \quad (3)$$

This research incorporates the mean squared error (MSE) function to evaluate the performance of the back propagation neural network. The objective function is as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (actual_i - predicted_i)^2 \quad (4)$$

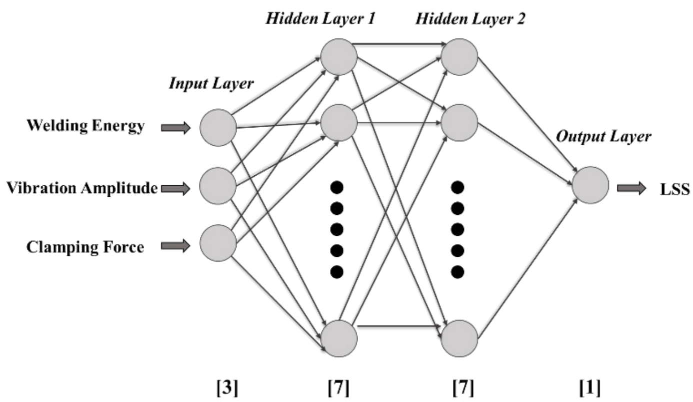

Figure 2 Architecture of the ANN

The number of iterations was set to 300, with a learning rate of 1% and a learning objective of 0.01. The Levenberg-Marquardt machine learning algorithm [14] was selected to train the ANN as this algorithm has demonstrated a high level of accuracy in similar work [8], [9]. The training was terminated when the MSE reached the learning objective or the maximum iteration value was reached.

The hyperparameters of the ANN were optimized but the model performed poorly with an average relative error of 21.3% between predicted and actual LSS. Thus, further refinement was required. The ANN was combined with a GA to optimize the initial weights of the network allowing for faster convergence. This ensures the learning objective is achieved but most importantly ensures the model is a representative of the global optimum. GA is an optimization algorithm inspired by the natural process of biological evolution [15]. The key features of a GA are population initialisation, fitness function, selection, crossover and mutation. Figure 3 illustrates the process flow for the GA integration within the ANN.

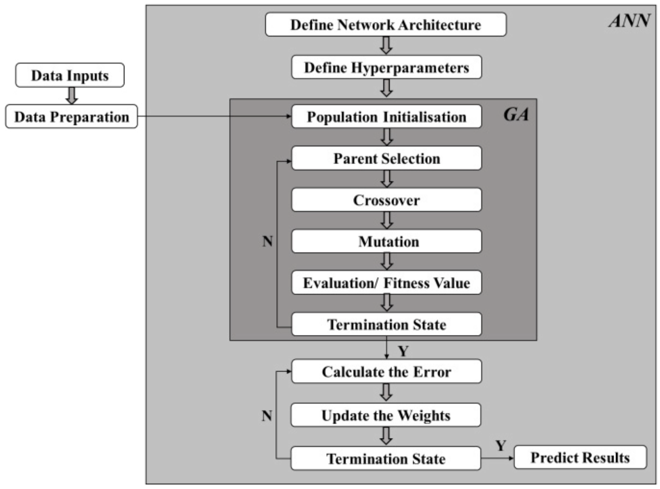

Figure 3 Flow chart for the hybrid GA-ANN method

4. Analysis

A further ten experiments (see Table 1) were conducted to evaluate the performance of the ANN on validation data. According to Table 1 the predicted error is within 250 N. The mean relative error for the validation data is 6.79%. However, the average error for all experimental data is 3.59%.

Table 1 Details of ten experiments used to Validate the ANN

Test	Energy (J)	Vibration amplitude (μm)	Clamping force (bar)	Actual LSS (N)	Predicted LSS (N)	Error (N)
1	1500	50	3	1248	1121	127
2	1500	60	2.5	1485	1595	-110
3	1500	60	3.5	1814	1711	103
4	2500	50	3	1744	1613	131
5	2500	60	2.5	1889	1835	54
6	2500	60	3.5	1709	1959	-250
7	3000	50	3	1579	1788	-209
8	3000	60	2.5	1480	1512	-32
9	3000	60	3.5	2280	2171	109
10	4000	60	2	2274	2249	25

Figure 4 displays a regression analysis between the actual and predicted results. The correlation coefficient (R) between the actual and predicted values (including training data) is 0.9827. The high correlation indicates that the is a strong relationship between the actual and predicted results.

Figure 5 represents a residual analysis that was also performed to further verify the accuracy of the model. The graph highlights similar errors throughout training and validation data suggesting an accurately fit model. The residual is defined as:

$$Residual_i = Actual_i - Predicted_i \quad (5)$$

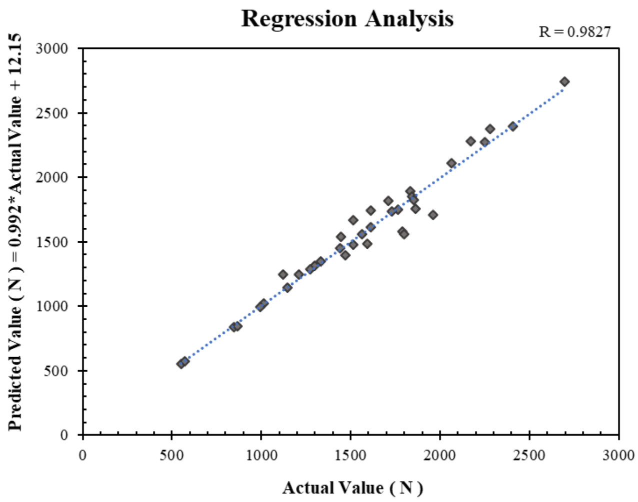

Figure 4 Regression analysis between predicted and actual results

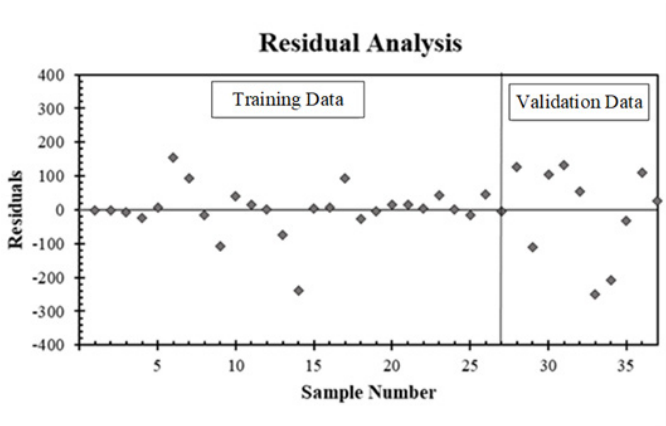

Figure 5 Residual Analysis

5. Conclusion

Parameter selection is a key area of research in ultrasonic welding due to the complexity of the welding mechanism. This study developed a hybrid machine learning architecture composed of a GA-ANN model for performance prediction. Initial weights of the model were optimised with a GA to ensure the global optimum was reached. The model was then trained on 27 sample experiments and validated on 10 sample experiments. The model's performance is satisfactory, with a mean relative error of 6.79% on validation data. This highlights the model's low generalisation error. The regression analysis demonstrated the strong relationship between the actual and predicted values for all experimental data with a high correlation coefficient of 0.9827. The regression and residual analysis both highlight average errors throughout training and validation data suggesting an accurately fit model. Future work includes developing a more refined model through increased input parameters. The refined model will be developed through a deep neural network that accurately defines what process information increases the model's accuracy and what creates noise within the model.

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Appendix A. Design of Experiments

Table A-1 displays the design of experiments with the data used to train the hybrid GA-ANN model.

Table A-1 Design of Experiments

Test	Energy (J)	Vibration amplitude (μm)	Clamping force (bar)	LSS (N)
1	1000	45	2	550
2	1000	45	3	570
3	1000	45	4	840
4	1000	55	2	842
5	1000	55	3	1020
6	1000	55	4	1670
7	1000	65	2	1539
8	1000	65	3	1751
9	1000	65	4	156
10	2250	45	2	1249
11	2250	45	3	1314
12	2250	45	4	993
13	2250	55	2	1397
14	2250	55	3	1557
15	2250	55	4	1447
16	2250	65	2	1851
17	2250	65	3	2373
18	2250	65	4	1824
19	3500	45	2	1144
20	3500	45	3	1349
21	3500	45	4	1289
22	3500	55	2	1734
23	3500	55	3	2107
24	3500	55	4	1611
25	3500	65	2	2392
26	3500	65	3	2740
27	3500	65	4	1559

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