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# PREDICTION OF WELD STRENGTH IN POWER ULTRASONIC SPOT WELDING PROCESS USING ARTIFICIAL NEURAL NETWORK (ANN) AND BACKPROPAGATION METHOD

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## ABSTRACT

In this presented work, an Artificial Neural Network (ANN) connected with the backpropagation method was employed to predict the strength of joining materials that were carried out by using an ultrasonic spot welding process. The models created in this study were investigated, and their process parameters were analyzed. These parameters were classified and set as input variables like applying pressure, time of duration weld and trigger of vibrating amplitude. In contrast, the weld strength of joining dissimilar materials (Al-Cu) is set as output parameters. The identification from the process parameters is obtained using several experiments and finite element analyses based on prediction. The results of actual and numerical are accurate and reliable; however, their complexity has a significant effect due to being sensitivity to the condition variation of welding processes. Therefore, an efficient technique like an artificial neural network coupled with the backpropagation method is required to use the experiments as input data in the simulation of the ultrasonic welding process, finding the adequacy of the modeling process in the prediction of weld strength and to confirm the performance of using mathematical methods. The results of the selecting non-linear models show a noticeable potency when using ANN with a backpropagation method in providing high accuracy compared with other results obtained by conventional models.

**Keywords:** *Ultrasonic seam welding process, artificial neural network, back propagation method, process parameters, prediction strength*

## 1. Introduction

Ultrasonic welding techniques remain one of the significant inescapable joining methods, cost-effective, robust and essential processes that apply to joining materials, polymers, and composites. They cover a wide range of manufacturing and industrial applications. The joining state of materials by ultrasonic is recognized by forming a solid-state condition at intimate surfaces without any fusion or melting [1-2]. Generally, an ultrasonic welding system consists of a driving piezoelectric transducer that converts the alternative current 50-60 Hz and raises to 20 kHz or above by means of the effect of piezo ceramic discs, boosting the second component, which is optionally added to increase the amount of vibration amplitude delivering by the transducer to the working area and to hold the welding rig securely and rigidly. In contrast, the last component described as an essential component of the welding system is a sonotrode or horn. Other supplementary components, such as fixing tools, screws and supporting anvils, are added to complete the ultrasonic welding system. The horn or working tool is critical as it is placed in such a manner to be in touch with the material being welded. The horn is designed in different shapes and dimensions to match the mechanism of producing high friction between contact surfaces is carried through exciting the horn by the transducer, which leads to creating relative motion, progressive shearing and plastic deformation, and then removing any unfavourable such as oxide layers and contaminants in order to bring an increasing area of clean metal to successfully weld [3]. The temperature developed during the welding process does not exceed the melting point of parent materials. In contrast, the process is completed rapidly within a few seconds, leaving the properties of joined materials unchanged. A typical schematic diagram of the ultrasonic configuration system for weld is shown in Figure 1.

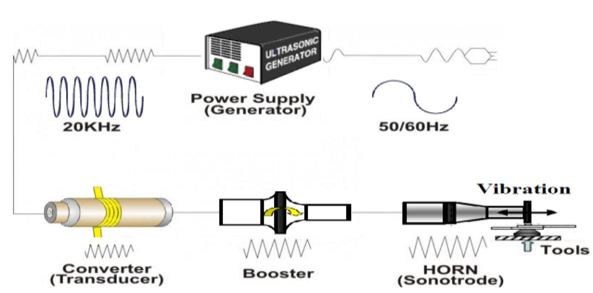


Fig. 1 Ultrasonic configuration system

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High vibrational performance of ultrasonic device depends on identifying many criteria, such as exciting the tools (booster and horn) at the operating frequency of the transducer and vibrating the horn with a frequency close to the resonant frequency of the operating system, ensuring good separation between tuning modes, avoid any losses during vibration and shifting back of stress concentration at horn tip. In the ultrasonic welding process, system parameters can be chosen based on the experience, trial and error or judgment of the welder or, to some extent, on the history of previous literature research [3]. To get weld, system parameters should be first set, such as welding (clamping) force, time duration of weld cycle and sufficient amount of vibration amplitude to ensure passing energy to the work area. These parameters are responsible for the type of joint strength and weld quality. Any change or mismatch in welding conditions may result in suppression in weld strength and then affect weld quality; therefore, to avoid that, it is reasonable to find a proper connection between weld strength and process parameters. For that reason, this study has suggested using the ANN with a back propagation method to predict the strength of joining materials by ultrasonic welding.

Many studies and research have been conducted on the bonding topics among the condition of solid-state joining processes. During the past decade, abundant research activities have covered the use of ultrasonic welding techniques in different areas and for numerous applications for predicting joint strength. Some of these previous works can be explained here as follows:

The prediction of weld strength is presented by a study which used an artificial neural network to complete that and combined this technique with a genetic algorithm to optimize the initial weight of ANN. The model was trained using the Levenberg-Marquardt algorithm to obtain high accuracy and lower errors for the experiment data [4]. Prediction of the quality joint is also contributed by research that implemented continuous ultrasonic welding of thermoplastic composites through training different neural networks. The accuracy ratio of predicting weld quality is recorded by 72%, which confirms the suitability approach for quality observation [5]. A study investigates the influence of joining parts on mechanical properties and focusing the intimate microstructure surfaces of joining aluminium and steel alloy sheet; the authors deduce an inverse relationship between the strength and the applying load, as excessive load lead to reduce friction created at the welding zone [6]. Optimizing the ultrasonic welding parameters for joining similar materials such as copper is carried out using the Taguchi technique for designing the experiments, which the study confirms that the parameters have affected joint strength; however, the strength exhibit less effective due to the influence of time and amplitude of welding process [3-4]. Another approach based on using the Taguchi method for welding dissimilar materials is presented to study the effect of welding pressure and ultrasonic energy on weld strength [7]. The extended of using Taguchi method with ANN is done on the study and optimize the selected parameters proposed for the turning machine, in which the investigation of parameters is obtained by employing an array in an orthogonal manner, the aspect ratio of signal concerning noise also use the variance to characterize the removal steel bar by carbide tool [8]. A contribution study on the effect of input parameters on the quality of weld bead geometry for submerged arc welding is carried out based on ANN with the backpropagation method; the data are successfully trained for the network structure of neurons layers to permit for predicting bead geometry and to reduce the error percentage of multiple tests, which the results show the viability of using ANN not only for prediction weld quality but also to be an efficient method for real-time work [9]. In addition, welding parameters are investigated on welded specimens made from (ABS) and (PMMA) polymers by ultrasonic welding; the weld strength is predicted using the ANN technique. While the similar study on predicting the tensile strength of welding aluminium to steel is identified by implementing ANN to examine the effect of welding parameters on joint strength [10].

Further studies have been published to show the adequacy of applying the ANN technique combined with various mathematical algorithms, such as multiple regression, forward and backward propagation methods, and linear and non-linear regression techniques. However, these studies are applied on different welding processes such as laser welding, metal gas inert welding, TIG/MIG welding, friction stir welding, and other types of the weld. Also, the above techniques are employed in various machining processes such as milling machines, turning machines and CNC machines to predict the strength of the joining parts [11-13]. After surveying many types of research, it is seen that part of previous studies has investigated the strength of weld using only the ANN technique or by combining it with different mathematical methods. Several studies have been carried out to focus on optimizing welding parameters and studying the joint strength of weldment, but most of these studies used conventional welding processes, while a few numbers of research concerned with the use of the ultrasonic welding process. Therefore, due to the limited work in the prediction of weld strength for joining parts ultrasonically. Building a

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model based on the principles of ultrasonic spot welding conjugate with the ANN and combined with the backpropagation algorithm is taken up for this work to study the feasibility of selecting ultrasonic parameters in predicting weld strength.

## 2. Experimental setup of the ultrasonic welding process

To apply the ANN technique linked with a mathematical algorithm for the prediction of weld strength, it is first required to prepare for suitable welding device that matches the study requirements. Therefore, getting a proper joint performance will normally depend on establishing a sufficient number of training tests directly generated by experiments. For that purpose, an ultrasonic welding machine was designed, built and assembled to produce several welds, the welder machine worked to cover a range of welding parameters with specification values (1000 W, 20 kHz). The ultrasonic horn material was selected from mild steel, and its dimensions were specified based on the application of spot welding, in which the horn was simulated precisely to vibrate at the half wavelength with the same frequency as the operating system (20 kHz) using finite element analysis (FEA), commercial code ABAQUS, and then the verification of vibrating horn was verified using experimental modal analysis (EMA) by diagnosis its excitation by means of 3D laser Doppler vibrometer instrument. Then the welding device was directly set up on the tensile machine to form the welding device, and other components such as knurled steel anvil, fixture tools and supplements were designed and assembled to the welding stack to form at the end the welding device. The benefit from the computerized equipment of the tensile machine and the controller with DAQ system will help to successfully operate the welding process. In this study, aluminium and copper specimens were prepared based on ASTM and BSI Standard codes [14-15], and the dimensions of all Specimens were carried out to have 55 x 10 mm with a thickness 0.5 mm. The overlapping area was left with specified dimensions equal 10 x 10 mm to match the surface area of the horn tip. Several experiments were carried out to examine weld strength and measure the failure load of lap shear tests at a tensile speed of 2.5 mm/min. The measure of maximum strength at the weld interface is recorded by the software program of the tensile machine and the triggering of the control panel connected with the DAQ system during the operation of the welding process.

**Figure 2 Setup of ultrasonic welding device and their accessories with generator, controller and sets of spot welded specimens**

In an ultrasonic welding system, the selection of input parameters have significantly affected the performance characteristics of weld strength. Therefore, a good consideration of these parameters may result in accepting weld strength. Generally, these input parameters are namely: welding pressure (clamping force), welding time (time of duration weld process) and displacement amplitude (amount of excitation at the horn tip). The actual range of ultrasonic input parameters were chosen carefully to set so that sound weld can be obtained. The interactions between input parameters were recognized by dividing it into three levels, which allow the factors and their levels to be set later in the design of experiments for the suggested models. Table 1 shows the factors and their levels proposed for this work.

**Table 1: Ultrasonic input parameters and their levels**

| Factor Levels | Welding Input Parameters Welding Pressure | Welding Time | Displacement Amplitude |
|---|---|---|---|
| | Bar | Sec | micron |
| -1, 0, +1 | 1.5, 3.0, 4.0 | 1.0, 1.5, 2.0 | 15, 27, 42 |

In the current work, the experiments of 30 successful trials were conducted through set three input

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parameters with three levels central design, while other trials were failed in the test or neglected. Many attempts were made to develop mathematical models to conduct the relationship between input parameters and weld strength. The developing models were examined with two different techniques, for example, neural network and multiple regression techniques which the input and output parameters were denoted by variables as follows:

X1 – Applying pressure (AP)
X2 – welding Time (WT)
X3 – vibration amplitude (VA)
X4 – welding strength (WS)

## 3. Modeling of weld strength using response surface and ANN

The response surface methodology (RSM) is considered an analytical technique that widely depends on mathematical and statistical concepts to model and analyze processes to result in extracted responses directly affected by adopting variables [16-17]. The method can also be used for experimental, ordinal or categorizing data to determine a correlation between variables [ ]. In addition, the RS method can be applied to predict the weld strength, so it was adopted in the presented work. A total of 30 trials, as tabulated in Table 2 were checked by means of use of the central design of experiment (DOE) for 0.5 mm thickness of spot welding dissimilar materials (Al-Cu) aluminium and copper specimens.

**Table 2: Experiments and RSM of weld strength for joining Al-Cu specimens**

| No. of Trials | US input Parameters | | | US Weld strength ($10^6$ N/m$^2$) | |
|---|---|---|---|---|---|
| | X1 bar | X2 sec | X3 µm | Exp. | Pred. |
| 1 | 1.5 | 1.0 | 15 | 1.24 | 1.44 |
| 2 | 1.5 | 1.0 | 15 | 1.62 | 1.87 |
| 3 | 1.5 | 1.0 | 15 | 1.38 | 1.22 |
| 4 | 1.5 | 1.0 | 15 | 1.78 | 1.34 |
| 5 | 1.5 | 1.0 | 15 | 1.98 | 1.94 |
| 6 | 1.5 | 1.0 | 15 | 1.88 | 1.77 |
| 7 | 1.5 | 1.0 | 15 | 1.72 | 1.44 |
| 8 | 1.5 | 1.0 | 15 | 1.81 | 2.03 |
| 9 | 1.5 | 1.0 | 15 | 1.28 | 1.18 |
| 10 | 1.5 | 1.0 | 15 | 1.16 | 1.33 |
| 11 | 3.0 | 1.5 | 27 | 1.65 | 1.43 |
| 12 | 3.0 | 1.5 | 27 | 1.75 | 1.55 |
| 13 | 3.0 | 1.5 | 27 | 1.86 | 1.77 |
| 14 | 3.0 | 1.5 | 27 | 1.92 | 1.88 |
| 15 | 3.0 | 1.5 | 27 | 1.89 | 1.60 |
| 16 | 3.0 | 1.5 | 27 | 1.33 | 1.81 |
| 17 | 3.0 | 1.5 | 27 | 1.38 | 1.66 |
| 18 | 3.0 | 1.5 | 27 | 1.49 | 1.39 |
| 19 | 3.0 | 1.5 | 27 | 1.21 | 1.66 |
| 20 | 3.0 | 1.5 | 27 | 1.19 | 1.25 |
| 21 | 4.0 | 2.0 | 42 | 1.98 | 1.66 |
| 22 | 4.0 | 2.0 | 42 | 2.35 | 2.29 |
| 23 | 4.0 | 2.0 | 42 | 2.02 | 2.22 |
| 24 | 4.0 | 2.0 | 42 | 1.98 | 2.03 |
| 25 | 4.0 | 2.0 | 42 | 2.15 | 1.99 |
| 26 | 4.0 | 2.0 | 42 | 1.98 | 2.05 |
| 27 | 4.0 | 2.0 | 42 | 2.20 | 2.12 |
| 28 | 4.0 | 2.0 | 42 | 1.98 | 2.10 |
| 29 | 4.0 | 2.0 | 42 | 1.88 | 2.01 |
| 30 | 4.0 | 2.0 | 42 | 1.99 | 1.80 |

A mathematical model was built according to the artificial neural network principle to initiate a learning map and set of ultrasonic input parameters corresponding to the weld strength. As the ANN technique is considered a powerful technique in determining a proper correlation between process parameters and output variables, this technique can also recognize linear and non-linear models and find a relationship for selecting data based on the concept of learn. These advantages make ANN simple, effective and low-cost [9]. The current work has performed a backpropagation (BP) combined with ANN to dominate the learning algorithm's forward and backward passes. In modelling ANN, the complexity normally faced by creating a model is how to reach optimum network architecture. To solve that, the model should have a number of layers which contains neurons arranged in such a manner to connect between actual and hidden layers, in which the parameters of the ultrasonic process were set as input layers: namely: applying pressure X1, welding time X2 and vibration amplitude X3 whereas weld strength (X4) was set as an output layer leaving other layers to be set as hidden layers [18]. The neurons of ANN consist of many activation elements that permit each neuron to connect directly to other neurons by using links. The (BP-ANN) model was designed according to the sufficient number of hidden layers to obtain a suitable network structure matching the prediction of weld strength [19]. The analyses were tested and confirmed using the MATLAB-NN toolbox. Then, the model of 30 experimental trials was trained with the aid of (BP) method to verify the non-linearity regression. A NN architectural model for the proposed ultrasonic spot welding process is shown in Figure 3.

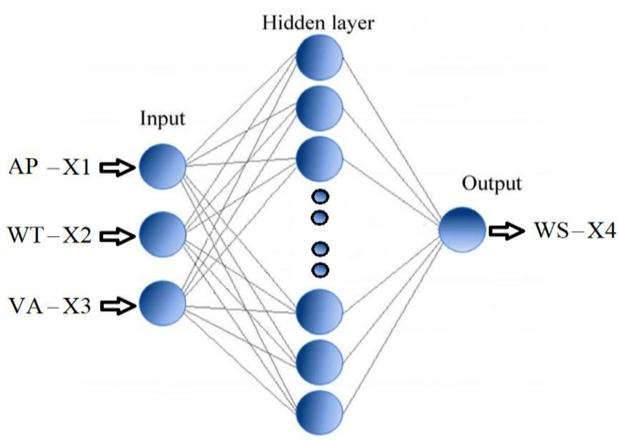


**Figure 3 Prediction of ultrasonic spot weld strength by (BP-ANN) architecture**

The model of weld strength was siplited into trained and tested data having 60 % and 40 %, respectively. A relationship between process parameters and predicting of weld strength were normalized based on apply the mathematical formula as follows: (WS - min Value) / (max. Value - min. Value), then a set of neurons were implemented (1-6) to fix the model architecture. The NN models were performed by extracting error criteria such as mean square error (MSE) and mean absolute error (MAE), which explained the effect of neuron numbers for training and testing, as seen in Figure 4 and Figure 5.

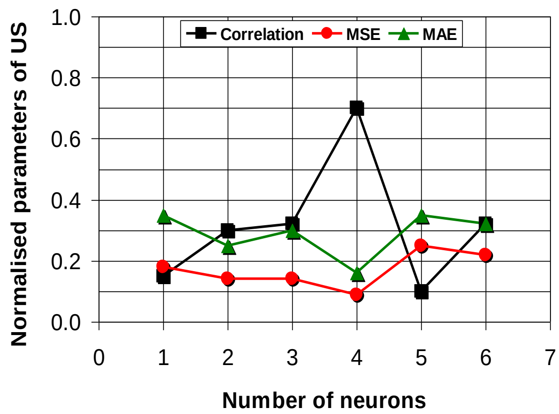


**Figure 4 Normalizing parameters for training data vesus the effect of neuron numbers**

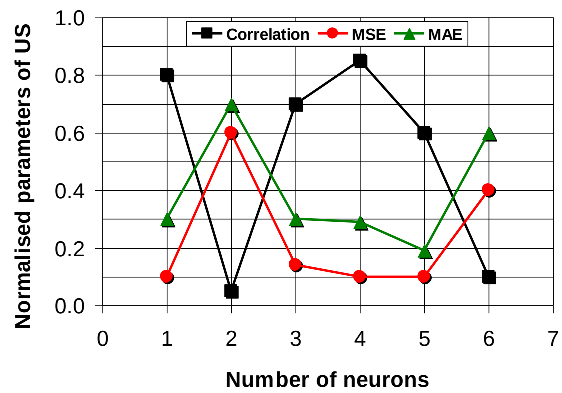


**Figure 5 Normalizing parameters for testing data vesus the effect of neuron numbers**

From the analyses of the figures above, it can be confirmed that maximum correlation values were recorded for training data (0.702) and for testing data (0.8975), while other values of (MSE) and (MAE) exhibit lower effect, which the observation of the values mentioned above indicates the reliability of trained model [20]. Therefore, the neural network analysis indicates a learning ratio for the developed models of predicting weld strength in which the rate of learning has a value of 0.898; the ratio was calculated based on the training of 30 trials. With several iterations up to 10000, this large number of iterations is necessary to minimize the percentage of error, lower the variation between experimental and prediction data and make the NN technique to be more reliable in predicting any process response such as weld strength. Figure 6 shows good agreements of close variation for R value compared with linear and fit curves, in which the trained lines indicate the acceptable prediction of process models.

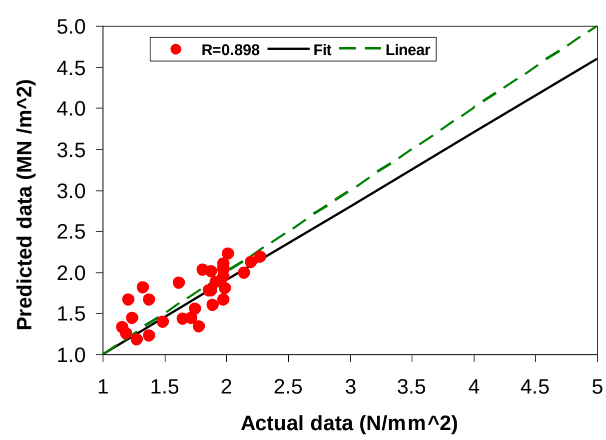


**Figure 6 Correlation between US actual data vs predicted data**

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An ultrasonic model for predicting strength was developed analytically based on the algebraic function of response surface methodology (RSM). A polynomial mathematical equation was built up to include three input process parameters (X1, X2 and X3) and one output process parameter (X4) as follows:

$$X4 = \sum_{i=1}^{3} A_j X_j + \sum_{i=1}^{3} A_{jj} X^2{}_j + \sum_{j=i+1}^{3} A_{jjj} X_j$$

The above functional terms are denoted by linear, quadratic and interaction, respectively.

## 4. Results and Discussion

The result of experiments for different process parameters combinations was analyzed by using Minitab software then the average percentage of these results was adopted by the term of mean prediction error for all BP-ANN tested models; also by this software, the developed model of predicting weld strength was determined on the assumptions of input process parameters. Some of the arbitrary results of estimated errors were tabulated in Table 3.

**Table 3: Percentage of error for experiments and predicted weld strength of joining Al-Cu specimens**

| Trials No. | US input Parameters | | | US Weld strength x10$^6$ | | % of error |
|---|---|---|---|---|---|---|
| | X1 bar | X2 sec | X3 µm | Exp N/m$^2$ | Pred. N/m$^2$ | |
| 2 | 1.5 | 1.0 | 15 | 1.62 | 1.87 | 15.4 |
| 8 | 1.5 | 1.0 | 15 | 1.81 | 2.03 | 12.2 |
| 13 | 3.0 | 1.5 | 27 | 1.86 | 1.77 | 4.83 |
| 19 | 3.0 | 1.5 | 27 | 1.21 | 1.66 | 37.2 |
| 22 | 4.0 | 2.0 | 42 | 2.28 | 2.18 | 4.38 |
| 28 | 4.0 | 2.0 | 42 | 1.98 | 2.10 | 6.06 |

Figure 7 explains the variations of prediction weld strength across the total number of trials carried out by actual ultrasonic spot welding and the estimated process using artificial NN combined with the BP algorithm. It was observed a very close in a variety of experimental and prediction data, also, it was seen that the weld strength has a noticeable effect due to low deviation of many trials, except a few trials are given large deviations under different sets of process parameters. Figure 8 testing the error percentage for all trials helped improve the efficiency of using neural network combined with the backpropagation method, confirm the predictability of weld strength and the ability to find suitable network architecture with the minimum prediction error. The mean prediction error shows good performance for reducing the percentage of error, which higher values having errors not exceeding 30 % except for two values.

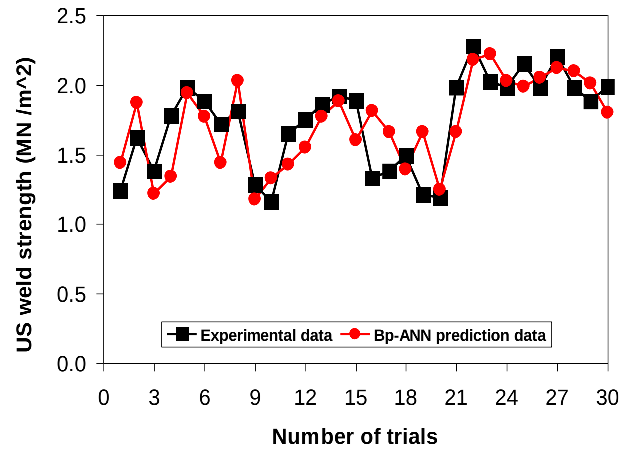


**Figure 7 Variation of experimental and prediction US data over the total number of trials**

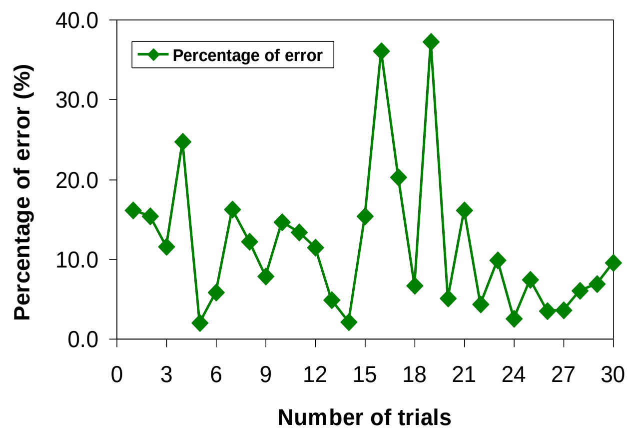


**Figure 8 Percentage of mean prediction error over the total number of trials**

The relationship between the actual combinations of ultrasonic input parameters with the estimated weld strength values calculated by RSM was illustrated by a contour surface plot as seen in Figure 9, in which the graphs were done by conducting data extracted from the peeled tests of joining Al-Cu specimens. Several notes were removed to confirm a prediction of weld strength, such as: the strength decreases with the increased weld pressure due to the lack of scrubbing motion generated at the the intimate surface (Figure 9-a). Figure 9-b reveals high sensitivity of weld strength across changes in vibrational amplitude along to changes in bonding time. It was inferred from the results that both the ultrasonic welding process and the use of ANN combined with BP mathematical method would improve the reliability and accuracy of prediction weld strengths.

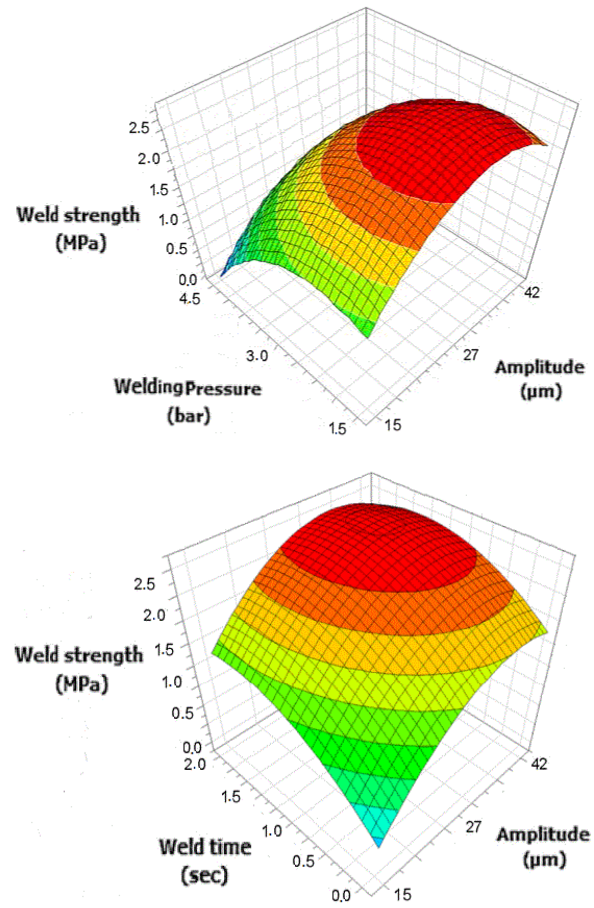


**Figure 9 Weld strength plot diagrams for the combination between actual and predicted input/output parameters**

## 5. Conclusion

In the current study, experimental results obtained successfully by the ultrasonic spot welding technique was used as an input parameter to develop a non-linear model based on the intelligence artificial neural network ANN concept connected with the backpropagation algorithm (BP) to allow for predicting weld strength. A set of experimental trials were carried out based on interactions between input/output parameters. Thirty trials of joined Al-Cu specimens were performed to train the non-linear network model, after split data into trained and tested, the models were built using ANN-BP and further using response surface methodology to predict the weld strength of network models. Prediction of weld strength by NN models was identified by extracting error criteria techniques, which are used to determine a suitable correction factor with a value equal to 0.898. It was inferred that using ANN-BP and further connected with RSM led to improve reliability and accuracy of prediction weld strength.

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