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Use of Artificial Neural Network to Evaluate and Forecast Selected Welding Parameters on Mild Steel Welded Joints Soldered by Tungsten Inert Gas

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ABSTRACT: Welded yield strength is designed to be large enough to handle all forces and pressures on the joint and is designed to be as strong as the tube itself. Hence, the objective of this paper was to investigate the use of artificial neural network (ANN) to evaluate and forecast selected welding parameters on mild steel welded joints soldered by tungsten inert gas (TIG) using sixty (60) experimental data generated by replicating the design matrix from the Central composite Design (CCD) used for the ANN modelling. The welding current, welding voltage and gas flow rate were selected as process parameters and yield strength chosen as Response. Data obtained show that the R-value (coefficient of correlation) for training shows of 95.8% closeness, 99.2% for validation and 93.1% for testing respectively. The overall R-value obtained is 95.1% which showed that the developed model can accurately predict the value of strength. Results also showed that ANN is a highly effective tool for prediction of the Yield strength in TIG Mild steel weld.

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Welding is the traditional means employed to join steel materials to produce a new structures. The integrity and quality of these structures becomes very important as it help to avoid structural failure and to prolong the service life. Steel materials are employed in the marine, construction, petroleum industries etc. According to Kim *et.al* (2003) who stated that in any welding process, process parameters play a key role in obtaining good weld quality. This help to improve the mechanical properties, metallurgical structures and the weld joint geometry. There are two main practical problems that engineers face in the welding process. The first is to determine the values of the process parameters that will give the best output. And the second is how to maximize manufacturing system performance with the available resources. To solve these problems, models need to be developed that can improve on this conditions during welding process. Raveendra and Kumar (2013) conducted an experiment to investigate the yield strength properties of a stainless steel plate at constant current and pulsed current at a high welding speed.

Their results shows that the constant current experiment has a higher yield strength than that of the pulsed current experiment. Sudhakaran *et al* (2011) applied artificial neural network model and simulated annealing algorithm for predicting depth of

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penetration, with welding current, welding speed, gas flow rate and welding gun as the process parameters. Man *et al* (2007) developed a model to predict the residual stress for dissimilar metal using the adaptive neuro fuzzy inference system (ANFIS). Campbell *et al* (2012) used artificial neural network model to predict the weld geometry. The experiment was performed with gas metal arc welding (GMAW) process, for determine weld penetration, length, and throat thickness. Choobi and Hanghpanahi (2012) formulated artificial neural network model to predict the angular distortion in butt welded stainless steel plates. Yasuhisa (2008) also predicted the welding distortions in fillet welds on mild steel plates using artificial neural networks model.

Abhulimen and Achebo (2014) applied artificial neural network model to predict weld quality in tungsten inert gas mild steel weld. In their investigation, they identified the most economical weld parameters that will bring about optimum properties and hardness of mild steel welded joints. Singh *et al*. (2013) applied artificial neural network for predicting impact strength in a shielded metal arc welding under the influence of external magnetic field. Singh *et al* (2012) used artificial neural network model to predict mechanical properties of mild steel welded joints. Ogbeide and Oriakhi (2023) applied Response surface methodology to predict corrosion rate in Tungsten inert gas mild steel welded joint. Ogbeide and Ebhota (2023) used response surface methodology to predict hardness strength in mild steel welded joint. Therefore, the objective of this paper was to investigate the use of artificial neural network (ANN) to evaluate and forecast selected welding parameters on mild steel welded joints soldered by tungsten inert gas (TIG)

MATERIALS AND METHODS

Experiment. Sixty (60) Experimental data were generated by replicating the design matrix from the Central composite Design (CCD) used for ANN modelling. These are welding current (I), shielding gas flow rate (Q) and welding voltage (v). The butt weld joint was used in this experiment. 100 **%** argon gas was used to carry out the welding experiment. The range of values of the process parameters was obtained from literature, and each parameter has two levels which comprise the high and low. This was carried out by varying one of the factors while keeping the rest as constant values. The working range of each process parameter was determined by inspecting the bead for a smooth appearance without any visible defect .The upper limit of a given factor was coded as (+1) and the lower limit was coded as (-1).This is expressed in Table 1

Table 1: Welding parameters and their levels

Parameters	Unit	Symbol	Coded value	Coded value
			Low(-1)	High(+1)
Current	Amp	A	90	190
Gas flow rate	Lit/min	F	11	15
Voltage	Volt	V	18	25

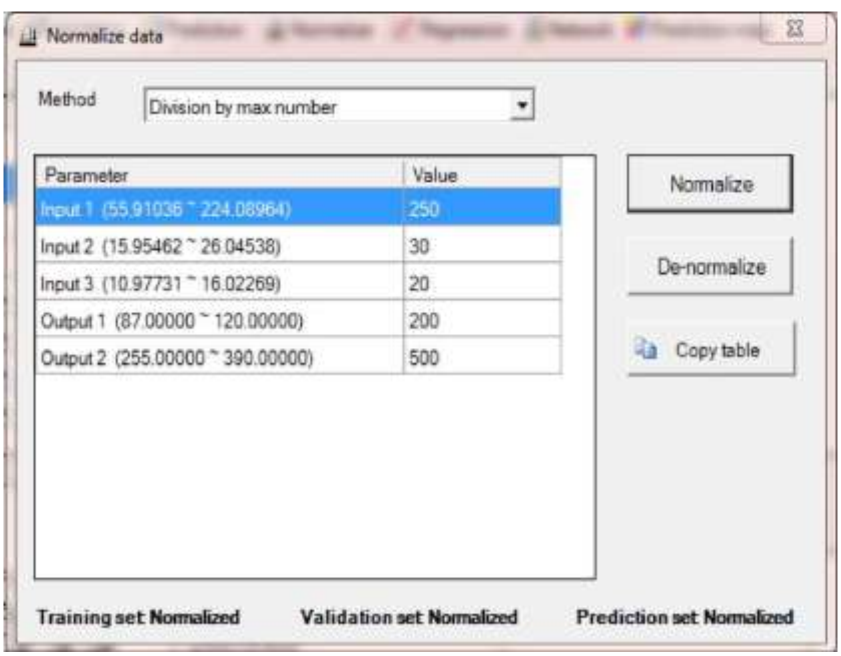

Fig 1: Parameters used in normalizing the raw data

The experimental results obtained was used as data for analysis. Predictive model such as artificial neural network (ANN) was employed for predicting the weld output. Sixty (60) experimental data generated by replicating the design matrix from the CCD was used for the neural network modelling. The experimental data were first normalized to avoid the problem of weight variation that may subsequently result in overtraining which is a major limitation in neural network modelling. Figure 1 shows a section of the normalized form of the data which has three input variables designated as In1, In2 and In3 representing current, voltage and gas flow rate and one output variable designated as out1 representing: the Yield Strength.

RESULTS AND DISCUSSION

Prediction of Yield Strength: The experimental results obtained is presented in table 2. The results was used as data for analysis. The network training diagram generated for the prediction of impact energy using back propagation neural network. From the network training, it was observed that the network performance was significantly good with a performance error of 4.99e-06 which is far lesser than the set target error of 0.01. The maximum number of iteration needed for the network to reach this performance was observed to be 11 iterations which is also lesser than the initial 1000 epochs. The gradient function was calculated to be 7.19e-05 with a training gain (Mu) of 1.00e-11. Validation check of six (6) was recorded which is expected since the issue of weight biased had been addressed via normalization of the raw data. A performance evaluation plot which shows the progress of training, validation and testing is presented in Figure 2. From the performance plot of Figure 2, no evidence of over fitting was observed. In addition similar trend was observed in the behavior of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criteria used to determine the training accuracy of a network. An error value of 1.8875e-05 at epoch 5 is an evidence of a network with strong capacity to predict the impact energy. The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in Figure 3. Back propagation is a method used in artificial neural networks to calculate the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contributions of each of the selected neurons. Lower error give a better results. Computed gradient value of 0.7.1943e-05 as observed in Figure 3 indicates that the error contributions of each selected neurons is very minimal. Momentum gain (Mu) was used to train the neural network. The value obtained must be less than one. Momentum gain of 1.0e-11 obtained shows a network with high capacity to predict the impact energy. The regression plot which shows the correlation between the input parameters (current, voltage and gas flow rate) and the target parameter (Impact energy) coupled with the progress of training, validation and testing is presented in Figure 4

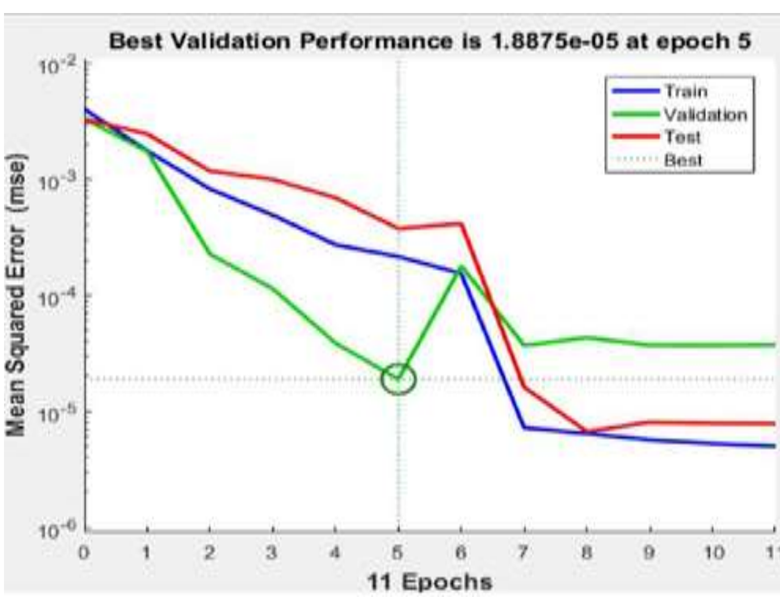

Fig. 2: Performance curve of trained network for predicting Yield Strength

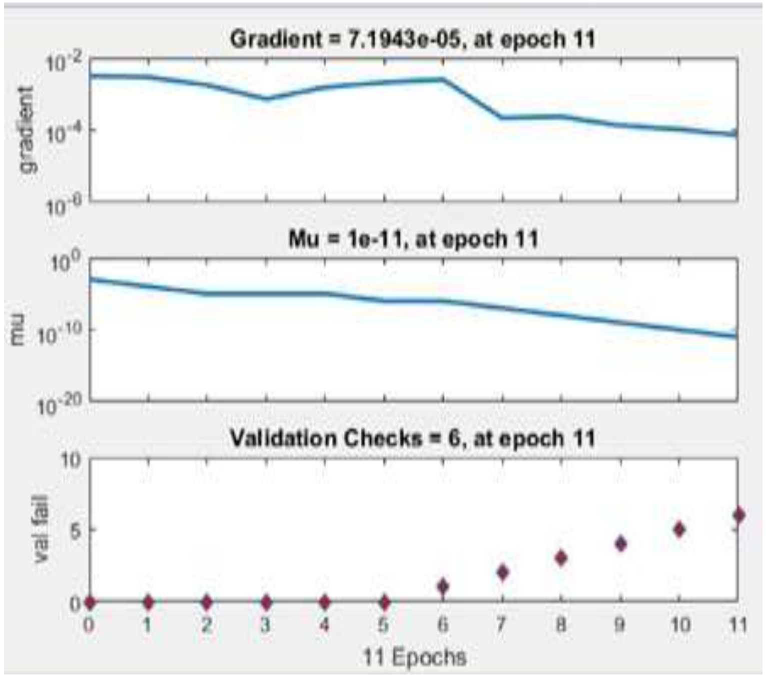

Fig 3: Neural network training state for predicting Yield Strength

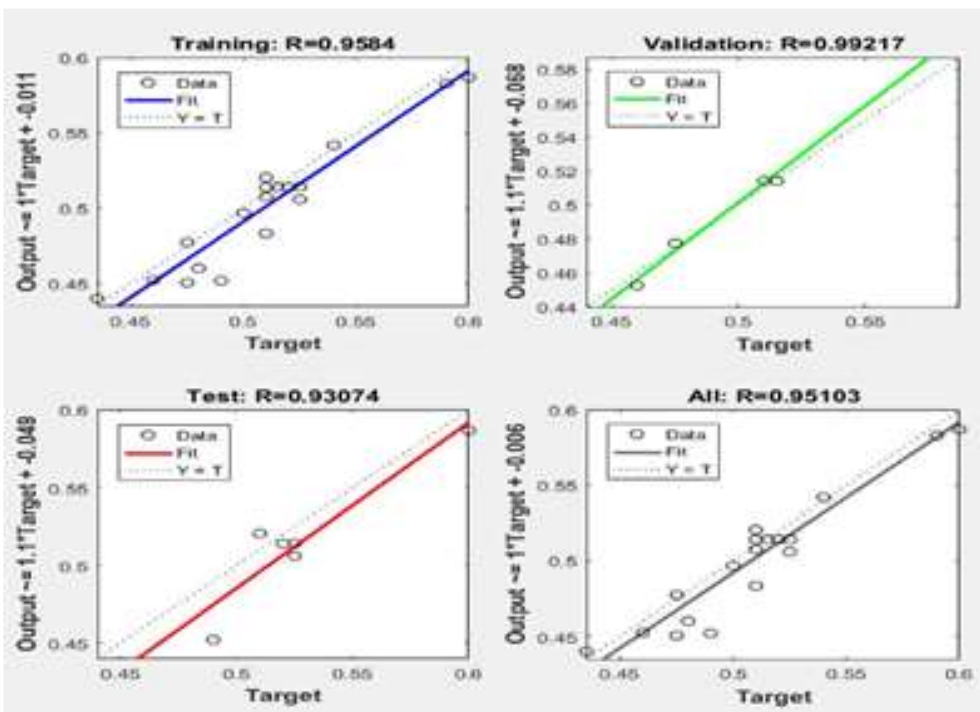

Fig 4: Regression plot showing the progress of training, validation and testing

Based on the computed values of the correlation coefficient (R) as observed in Figure 4. It was concluded that the network has been accurately trained and can be employed to predict the Yield Strength as shown in table 2. The Experimental Results obtained shows that current, voltage and welding speed and their interactions have major effects on the yield strength and the impact energy in TIG welding. The study used the artificial neural network (ANN) in predicting the yield strength in TIG welding of mild steel plates and the results are in agreement with literature. Campbell *et al* (2012) reported the use of ANN to successfully predict weld geometry. Sudhakaran *et al* (2011) and kim *et al* (2003) Have also used the ANN method to predict various welding output responses. In this study, twenty experimental runs were carried out, each run comprising the current, voltage and gas flow rate, were used to join two pieces of mild steel plates measuring 60 x40 x10 mm. The yield strength was measured. The neural network architecture comprises, three (3) inputs, one (1) output, twenty (20) neurons in the input layers and two (2) neurons in the output layer. The input layer uses a sigmoid transfer function while the output layer uses a linear transfer function. Lavenberg- Marquardt algorithm was used for the training (MSE) performance. The plot has three lines because the 30 input and target vectors are randomly divided into three sets, 70% of the data were used for training, 15% of the data were used to validate and the remaining 15% of the data were used for testing. A performance evaluation plot showed that both the test data set and the validation data set have similar characteristics. There is no evidence that overfitting occurred. The best validation performance was 0.48429 and occurred at epoch five (5). Figure 4 shows the linear regression plot between network output and experimental data. The coefficient of correlation (R-value) for training shows 95.8% closeness, 99.2% for validation and 93.1% for testing respectively. The overall R-value is shown to be 95.1%.

Table 2: Experimental and Predicted Results

Run No.	Current (A)	Voltage (V)	Gas Flow Rate (L/min)	Yield Strength Experimental Results	Yield Strength Predicted Results
1	140.0000	21.0000	13.5000	610.0000	615.0000
2	140.0000	21.0000	13.5000	402.0000	400.0000
3	140.0000	21.0000	13.5000	402.0000	404.0000
4	140.0000	21.0000	13.5000	455.0000	460.0000
5	140.0000	21.0000	13.5000	575.0000	581.0000
6	140.0000	21.0000	13.5000	580.0000	577.0000
7	55.9104	21.0000	13.5000	610.0000	600.0000
8	224.0900	21.0000	13.5000	402.0000	400.0000
9	140.0000	15.9546	13.5000	402.0000	411.0000
10	140.0000	26.0454	13.5000	402.0000	409.0000
11	140.0000	21.0000	10.9773	420.0000	422.0000
12	140.0000	21.0000	16.0227	444.0000	435.0000
13	90.0000	18.0000	12.0000	402.0000	412.0000
14	190.0000	18.0000	12.0000	532.0000	540.0000
15	90.0000	24.0000	12.0000	500.0000	506.0000
16	190.0000	24.0000	12.0000	610.0000	602.0000
17	90.0000	18.0000	15.0000	500.0000	512.0000
18	190.0000	18.0000	15.0000	618.0000	625.0000
19	90.0000	24.0000	15.0000	370.0000	373.0000
20	190.0000	24.0000	15.0000	344.0000	328.0000

*Conclusion***:** This study was carried out to investigate the performance of artificial neural network (ANN) in the prediction of yield strength in Tungsten inert gas mild steel weld. Result of the study have shown that the ANN is a highly effective tool for the prediction of the yield strength in TIG mild steel welding with a high value of coefficient of determination (R – squared value) which was very close to one which implies that the model developed was adequate and robust.

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