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Prediction of Impact Energy of TIG Mild Steel Welds Using ANN

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Abstract
The present trend in the fabrication industries is the use of automated welding processes to obtain high production rates and high quality output.TIG welding, happens to be the best welding method employed in the manufacturing industry. one of the problem facing the fabrication industry is the control of the process input parameters to obtain a good welded joint . however it is essential to establish the relationship between process parameters and weld quality output to predict and control weld bead quality .The aim of this study is to predict the impact energy of TIG mild steel welds using ANN.In this study, twenty experimental runs were carried out, each experimental run comprising the current, voltage and gas flow rate, the TIG welding process was used to join two pieces of mild steel plates measuring 60 x40 x10 mm , the impact energy was measured respectively. Thereafter the data collected from the experimental results was analysed with the ANN. The experimental results for the impact energy was analyzed with the Artificial Neural Networks. The overall R-value is shown to be 98.7%. The best validation performance is 0.48429 and occurred at epoch five (5). The coefficient of correlation for training shows of 99.9%closeness ,99.4% for validation and 89.8% for testing respectively.

1. Introduction

Tungsten inert gas (TIG) welding is also called the gas tungsten arc welding (GTAW) is a welding process that is widely used in modern industries for joining either similar or dissimilar materials. This process uses a non consumable tungsten electrode which has a very high melting temperature and has advantages of producing very high quality weld, low heat affected zone, and absence of slag . A common problem that has faced the fabrication industry is the control of the process input parameters to obtain a good welded joint with the required bead geometry and weld quality with minimal detrimental residual stresses. Sudhakaran et al(2011) developed an artificial neural network model for predicting depth of penetration, he also develop another model using simulated annealing algorithm to optimize the depth of penetration, the process parameters includes welding current, welding speed, gas flow rate and welding gun angle and the target response was depth of penetration. The fractional factorial experimental matrix was developed to guide in conducting the experiments with one output parameter was which resulted in 125 experimental runs .The MATLAB software was used to develop the ANN model, the result showed that the network 4-15-1 predicted depth of penetration more accurately. The optimized process parameters gave an optimum value of 3.778mm for depth of penetration, and a correlation model between the process parameters and depth of penetration was developed.

Lightfoot (2005)developed a model using the Artificial Neural Networks to predict Weld-Induced Deformation in Ship Plate, the model was used to study factors affecting the welding distortion of plates with thickness 6-to 8-mm , the experiment was conducted with DH 36 grade steel plate . Martin (2010) Studied the corrosion behavior of AISI 304 austenitic stainless steel. He used the Artificial Neural Network to predict the influence of the welding parameters of resistance spot welding. Choobi and Hanghpanahi(2012) developed a neural network model to predict the angular distortion in butt welded 304L stainless steel plates. He used the Finite Element Method to develop a wide range of training data of plate dimension in butt welds.Yasuhisa (2008) employed the artificial neural networks model to predict the welding distortions in fillet welds of mild steel plates.

2. Materials and Method

The method of achieving the objectives of the research is explained in this chapter. It comprises of the following:

(i) research design
(ii) population
(iii) Sampling technique
(iv) Method of data collection
(v) Models employed
(vi) Method of data analysis
(vii) Model validation
(viii) Model adequacy

2.1 Research design

Experimentation is a very important part of scientific study, and designing an experiment is an integrated component of every research study. In order to get the most efficient result in the approximation of polynomial the proper experimental design must be used to collect data.

The Central Composite Design(CCD) was developed for this study using the design expert softwareThis design is for any input parameters considered within the range of 3- 5 levels.

The key parameters considered in this work is gas flow rate (f) welding current (i) welding voltage (v) welding speed and the output parameters are the weld undercut and reinforcement.

The range of values of the process parameters was obtained from the open literature accessed, and each parameter has two levels which comprise the high and low .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	180	240
Gas flow rate	Lit/min	F	16	22
Voltage	Volt	V	18	24

2.2 Population

30 pieces of mild steel plate measuring 60mm in length, 40mm in width and 10mm thickness was used for the experiment. This experiment was repeated 30 times

2.3 samples and sampling technique

The tungsten inert gas welding equipment was used to weld the plates after the edges have been beveled and machined

2.4 Experimental procedure

Mild steel plate of thickness 10 mm was selected as material used for the experiment. The mild steel plate was cut with dimension of 60 mm x 40 mm with the help of power hacksaw and grinded at the edge to smoothen the surfaces to be joined. The surfaces of the coupon were polished with emery paper,thereafter the mild steel plates were fixed on the work table with flexible clamp to weld the joints of the specimen.A TIG welding process was used with Alternate Current (AC) to perform the experiments as it concentrates the heat in the welding area, using 100% argon gas as the shielding gas, thereafter the impact energy was measured.

2.5 Models Employed

In this study the artificial neural network methods (ANN) was employed in the prediction of impact energy

Model development

Figure 1 shows variation in mean square error with respect to epochs. The training, test and validation data sets follow the same pattern. It is clear from figure that as we keep on increasing the numbers of epochs for training, testing and validation, the error rate keeps on decreasing.

For the training data set, the mean squared error decreases as we move from epoch 0 to epoch 3. Subsequently, the MSE remained constant. The best validation performance is 147.9453 at epoch 2.

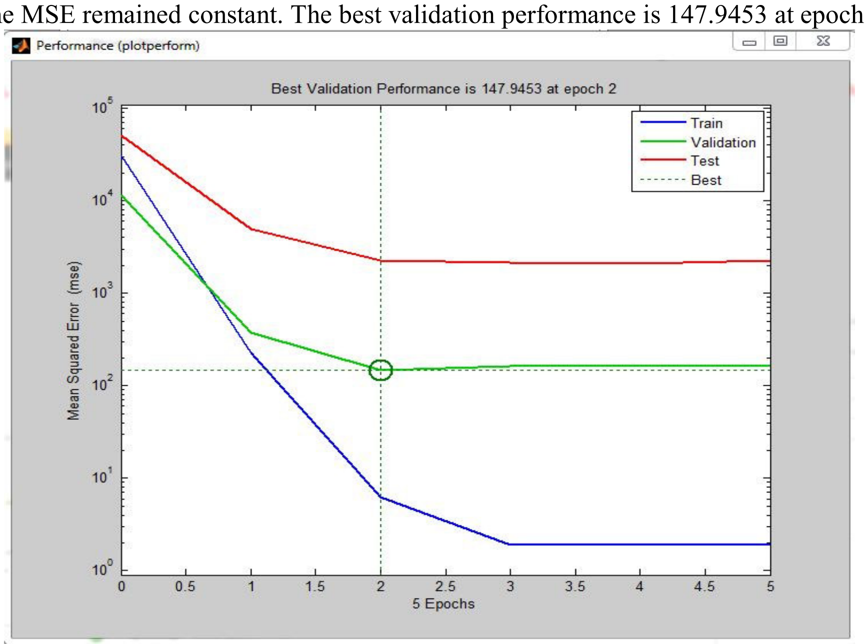

Fig 1: network performance

Model validation
Fig 2 is the regression plot of the neural network analysis. The R-values for training, test, validation and overall are respectively 0.99994, 0.99467, 0.89801 and 0.98759. The results from the neural network are show in table 4.20 along with the corresponding residuals.

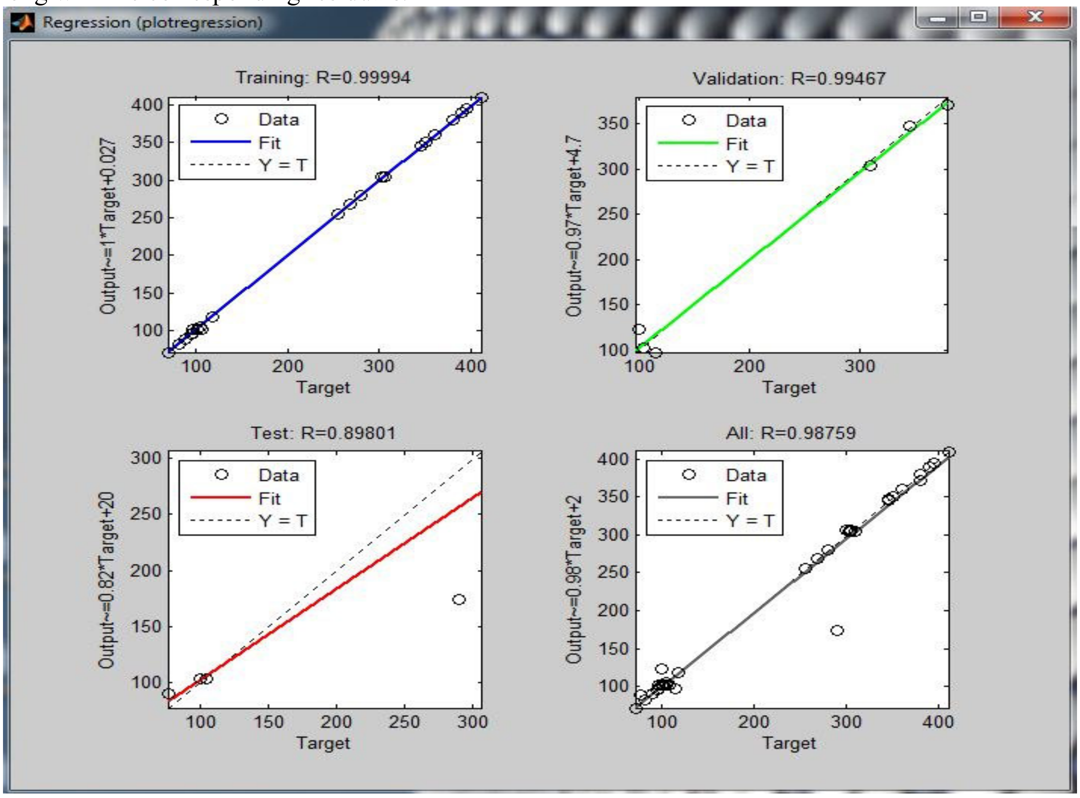

Fig 2: Regression plot

Results And Discussion
Table 3: results of experimental and ANN model predictions

INPUTS			EXPERIMENTAL	ANN
I (A)	V (V)	GFR (mm3/min)	CVN (J)	CVN (J)
90.00	18.00	13.00	90.00	90.72
160.00	18.00	13.00	98.00	97.17
90.00	22.00	13.00	115.00	98.83
160.00	22.00	13.00	100.00	123.28
90.00	18.00	15.00	83.00	83.50
160.00	18.00	15.00	105.00	105.06
90.00	22.00	15.00	95.00	94.35
160.00	22.00	15.00	77.00	89.47
64.38	20.00	14.00	82.00	82.80
185.62	20.00	14.00	95.00	94.63
125.00	16.54	14.00	102.00	102.80
125.00	23.46	14.00	118.00	117.96
125.00	20.00	12.27	102.00	102.35
125.00	20.00	15.73	72.00	72.29
125.00	20.00	14.00	105.00	102.99
125.00	20.00	14.00	100.00	102.99
125.00	20.00	14.00	98.00	102.99
125.00	20.00	14.00	105.00	102.99
125.00	20.00	14.00	108.00	102.99
125.00	20.00	14.00	102.00	102.99

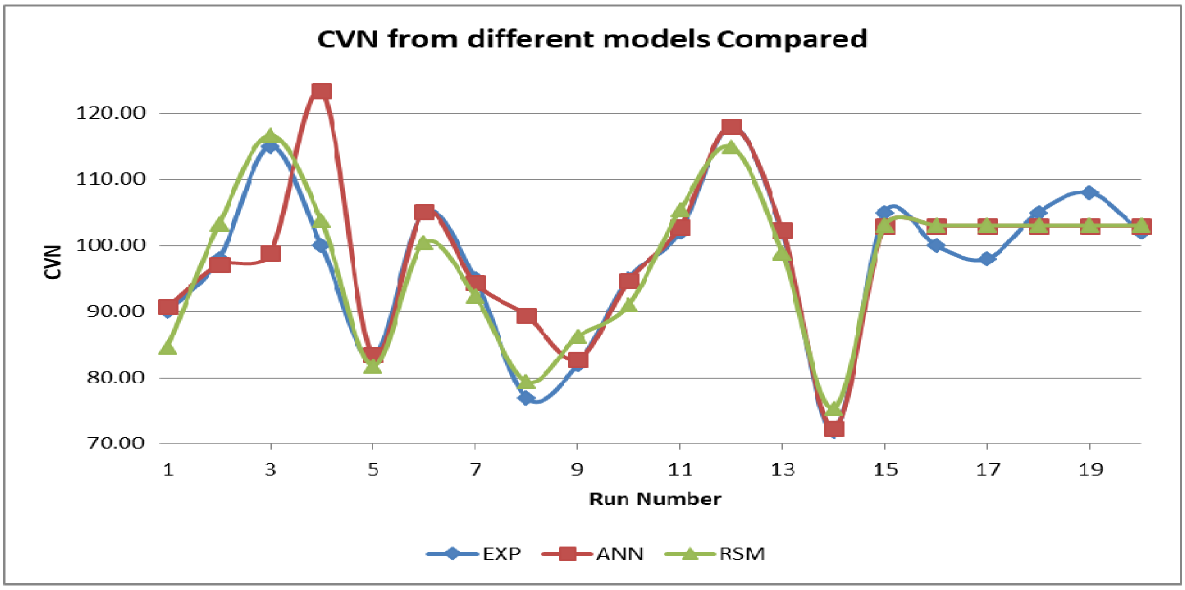

Fig 3:CVN from different models Compared

both the artificial neural network and the Response surface methodology models fit well. However the RSM model Provided a better overall fit to the experimental data than the ANN. At this point, the predicted value of 115.27 from RSM is very close to the experimental value of 115 and is in contrast to 97 from ANN

The experimental results for the impact energy was analyzed with the Artificial Neural Networks. Current, voltage, welding speed and gas flow rate are factors used to determine the output of weld. The neural network architecture comprises, three (3) inputs, two (2) outputs, twenty (20) neurons in the hidden layers and two (2) neurons in the output layer. 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 how well the network memorizes the training.,while15% of the data were used for the 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 is 0.48429 and occurred at epoch five 5. The R-value (coefficient of correlation) for training shows of 99.9%closeness ,99.4% for validation and 89.8% for testing respectively. The overall R-value is shown to be 98.7%. For the impact energy the artificial neural network methodology models fit well.

Conclusion

Research studies have been done to improve the quality of TIG welding using the artificial neural network method. The tensile strength of the TIG weld is influenced by the welding process parameters. The welding current and voltage has a very strong influence on the tensile strength of the weldments.

The experimental results for the impact energy were analyzed with the Artificial Neural Networks. The best validation performance is 0.48429 and occurred at epoch five (5). Figure 4. shows the linear regression plot between network output and experimental data. The R-value (coefficient of correlation) for training shows of 99.9%closeness ,99.4% for validation and 89.8% for testing respectively. The overall R-value is shown to be 98.7%. For ultimate tensile strength, the artificial neural network method models fit well. However the RSM model Provided a better overall fit to the experimental data than the ANN.

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