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Optimization and Prediction of Ultimate Tensile of TIG Mild Steel Welds Using ANN

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Abstract
TIG welding, is about the most popular welding method, which finds its applications in the fabrication industry. The integrity and service life of engineering structures is a very important factor in the welding technology sector, one of the problem facing the fabrication industry is the control of the process input parameters to obtain a good welded joint . Research has shown that one of the practical ways to improving on weld qualities is to optimize the input process parameters. The aim of this study is to predict the ultimate tensile strength 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 tensile strength was measured respectively. Thereafter the data collected from the experimental results was analysed with the ANN. The experimental results for the ultimate tensile strength was analyzed with the Artificial Neural Networks. 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 ultimate tensile strength, 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.

1. Introduction
TIG welding, is about the most popular welding method, which finds its applications in industrial environments. Evolving microstructure of welds in turn depends on the heating cycle arising during the welding, composition of the welded alloy, cooling condition, and the filler material. 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. According to Myers et al(1989) many industries today, now apply the Response Surface Method in formulating new products, especially in the chemical engineering industries,where there is need for process optimization.

Oehlert and Gary(2000) described the response Surface Methods as models that works continuously with treatments so as to achieve an optimum goal, he mentioned that the RSM is a very good optimization technique and has one common goal of determining the optimum response of the process. He mentioned that the RSM has a second goal,which is to understand how the response changes in a particular process, the response Surface Methods can be expressed graphically in the form a saddle ,ridge ,hill and valley lines.

Khoo et al(2000) studied the integration between the RSM and GAs so as to determine the near optimal values in response surface design. They presented a framework of the prototype system. A pseudo-objective function, which can be used to deal with one response and two response problems, was derived. The prototype system was validated 94 using three case studies. Comparative studies showed that both the prototype system and the Design Expert, which is a commercial software package, produced similar results.

Alvarez et al (2009) reported that GAs are applied in RSM in several situations where an optimization technique is needed.Chen et al (2005) created response surface models through regression on experimental data and applied the SQP and GAs on the models so as to optimize the processing conditions of dairy tofu. Both techniques were able to determine the optimal conditions for manufacturing these products.

Ozcelik and Erzurumlu(2005) presented an optimization method using RSM and GA to minimize the warpage on thin shell plastic parts. Kim et al (2002) proposed a method to optimize the variables for an arc welding process using RSM. Correia et al (2005) presented a comparison between GAs and RSM techniques in the gas metal arc welding (GMAW) optimization. Optimization of input process parameters can be done using mathematical methods, hence the Artificial neural network was used to obtain optimum model to predict the output quality of the weld.

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 tensile strength was measured.

2.5 Models Employed

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

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.

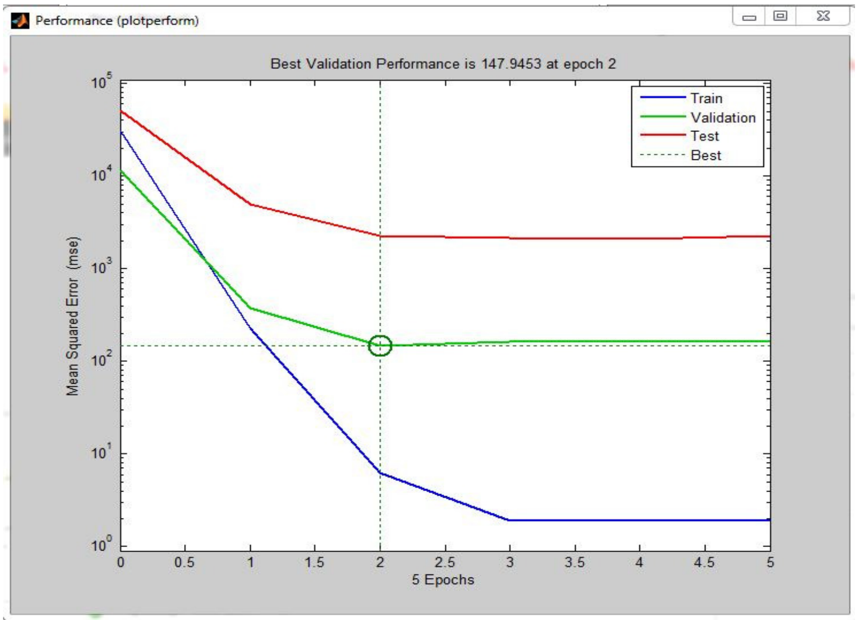

Fig 1: Network performance

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.

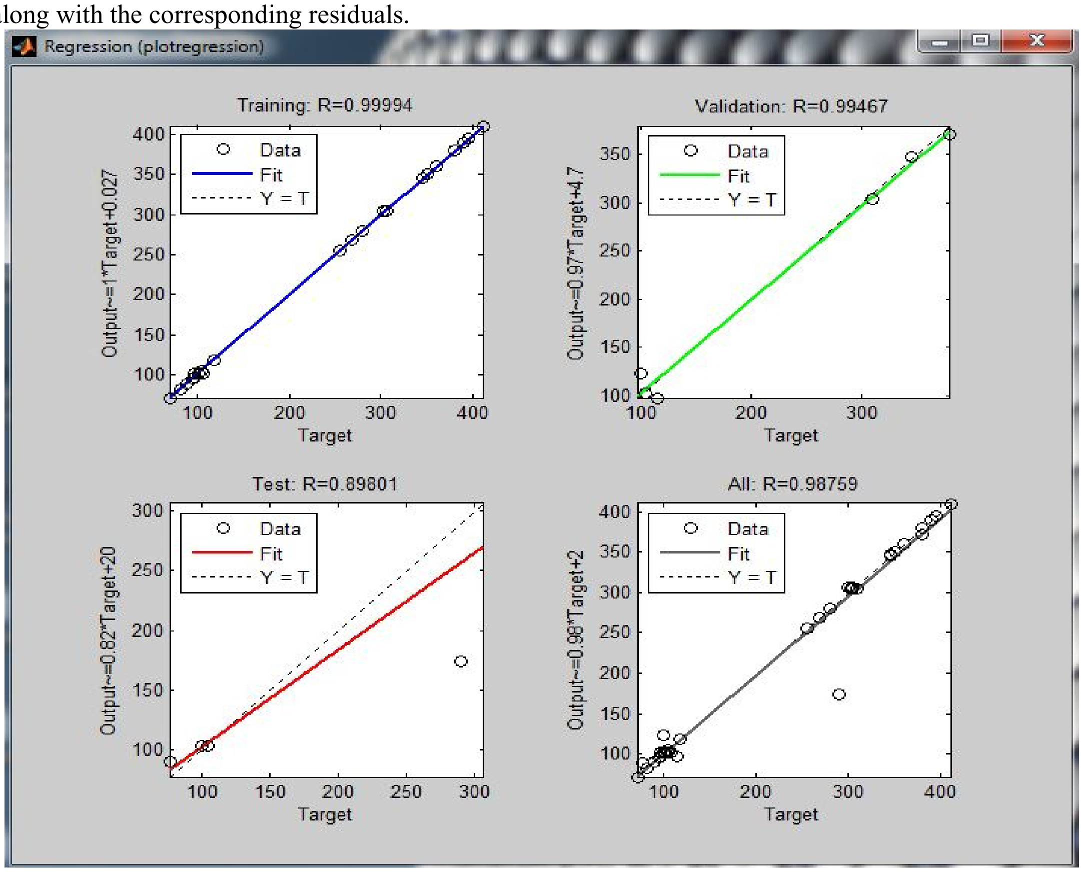

Fig 2: Regression plot

Results And Discussion

Table 3: results of experimental and ANN model predictions

INPUTS			EXPERIMENTAL		ANN
I (A)	V (V)	GFR (mm3/min)	UTS (Mpa)		UTS (Mpa)
90.00	18.00	13.00	410.00		413.40
160.00	18.00	13.00	350.00		351.19
90.00	22.00	13.00	380.00		372.35
160.00	22.00	13.00	346.00		342.90
90.00	18.00	15.00	350.00		352.26
160.00	18.00	15.00	268.00		270.44
90.00	22.00	15.00	345.00		343.17
160.00	22.00	15.00	290.00		173.70
64.38	20.00	14.00	360.00		362.23
185.62	20.00	14.00	255.00		250.21
125.00	16.54	14.00	394.00		400.05
125.00	23.46	14.00	390.00		387.23
125.00	20.00	12.27	380.00		380.58
125.00	20.00	15.73	280.00		278.47
125.00	20.00	14.00	300.00		306.50
125.00	20.00	14.00	305.00		306.50
125.00	20.00	14.00	305.00		306.50
125.00	20.00	14.00	310.00		306.50
125.00	20.00	14.00	303.00		306.50
125.00	20.00	14.00	305.00		306.50

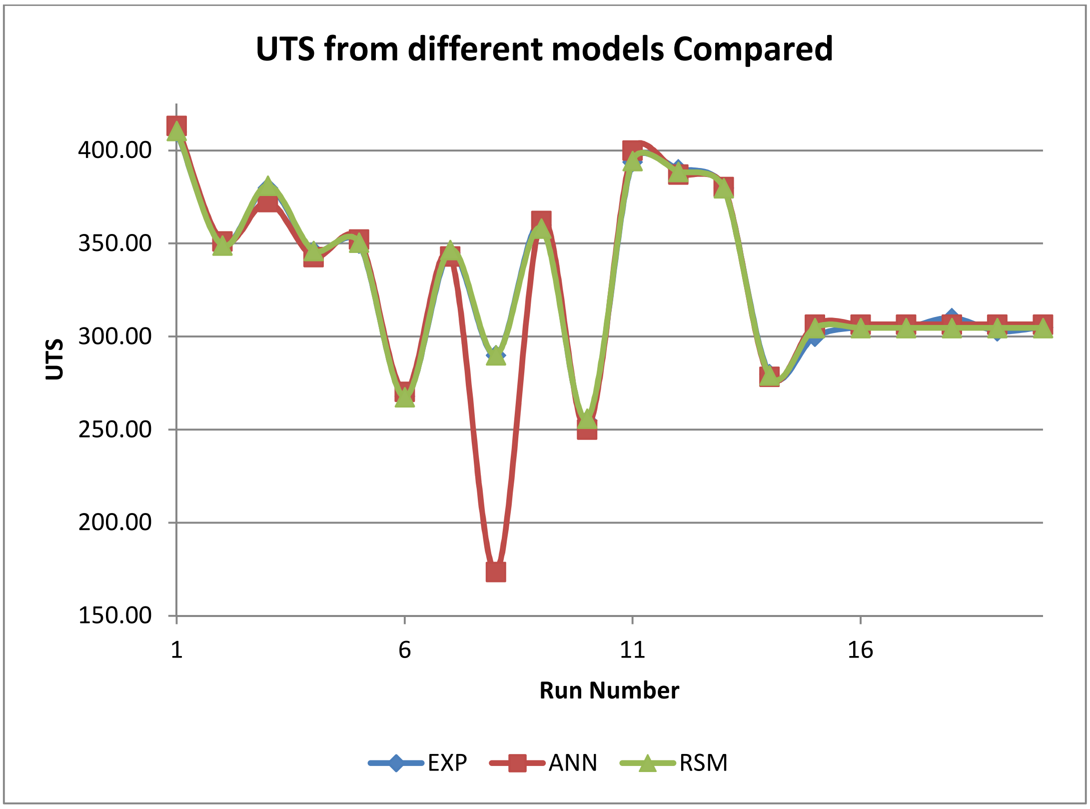

Fig 3:UTS from different models Compared

For ultimate tensile strength, 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 290.13 from RSM is very close to the experimental value of 290.00 and is in contrast to 173.70 from ANN

The experimental results for the ultimate tensile strength 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 ultimate tensile strength, both 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 ultimate tensile strength and 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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