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Experimental Investigation to analyse the Mechanical Properties of Weld Strength Factor Performed by TIG Welding

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ABSTRACT

The study presents, mild steel plate, cut with dimensions of 60 mm x 40 mm, then welded with 100% argon gas by the TIG welding using design of experiment, Response Surface Methodology (RSM) and Artificial Neural Network optimization techniques. Welding current, gas flow rate, and voltage, have been selected as the process parameters during the TIG welding process. The effects of these process parameters on the weld strength factor were identified using analytical and computational intelligence techniques. The design of experiment, and Artificial Neural Networ optimization techniques were used to optimize the effect on Weld Strength Factor of the welded joints. An orthogonal array of the central composite design was prepared by the design of experiment (DOE) methodology in which experiments were performed duly as per this orthogonal array obtained. The 210.00A, 22.66 V, and 20.00 gas flow rate optimum setting of input parameters provides the better results for the weld strength factor. This solution was selected by design expert as the optimal solution having a desirability value of 0.880. The study reveals the successful use of artificial neural networks in predicting the weld strength for tungsten inert gas welding of mild steel plates. The mean square error was used to measure the performance of the network in each run. The mean square performance index for the network is a quadratic function. The input data are randomly divided into three sets. 70% are used to train the network, 15% are used to validate the network performance and 15% are used for the test. The validation of the network model produced a correlation value of 94.0% with a mean square error of 1.040E-4. the testing of the network model produced a correlation of 97.7% with mean square error 1.003E-5. The performance plot showed that the model developed was learning, which is expected of a very good network. The artificial network model produced predicted values for the weld strength of which the predicted values and the experimental values of the responses, closely fit and are in reasonable agreement with a high coefficient of correlation.

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1. INTRODUCTION

Welding is the process of joining two metals by fusing the base metal and by adding a filler material over the surface of molten metal to form a strong bonding on metals. In tungsten arc welding the tungsten electrode with constant weld power supply is used to generate electric arc between the electrode and the workpiece which create resultant heat to form the weld. Welding is an efficient and economic method for permanent joining of metals (Naik and Reddy, 2018). Currently, TIG welding is an effective welding process to manufacture good quality structural components with great industrial potential. It is an arc welding process in which coalescence of material is accomplished by the application of heat generated by an electric arc struck between the non-consumable tungsten electrode and workpiece. During welding, the faying surface of the material is melted and solidified, and the weld pool is protected from atmospheric contamination by an inert gas purging out from the TIG torch (Kamlesh et al., 2022). TIG welding is the most common operation use for joining of two similar or dissimilar metals with heating or applying the pressure by using the filler material. TIG welding technique is used in several industries like automobile, aerospace, marine, etc. due to its quick and precise process (Himanshu et al., 2019). Tungsten Inert Gas (TIG) or Gas Tungsten Arc Welding (GTAW) process is extensively used for joining thin sections of stainless steel. However, it is not useful in joining thick sections in a single pass (Dipali et al., 2021). In tungsten inert gas arc welding the arc is produced by the electric supply which forms between the tungsten electrode and the base metal. Though other welding process the electrode melts to form weld but in gas arc welding point of base metal where weld is carried out is transformed in to weld pool by the arc. The filler material is manually added for TIG welding, and the molten metal is allowed to cool (Naik and reddy, 2018). Filler is used when welding together metals with high melting points to prevent cracking. In addition, highly corrosive resistant alloys when welded to thicker wall material require a filler wire. Finally, when dissimilar alloys are being joined a filler wire is needed. Metals with a thickness of more than 6 mm require the use of filler wire during welding with TIG welding process. Figure 1 shows a schematic diagram of the TIG welding process incorporated with the filler rod.

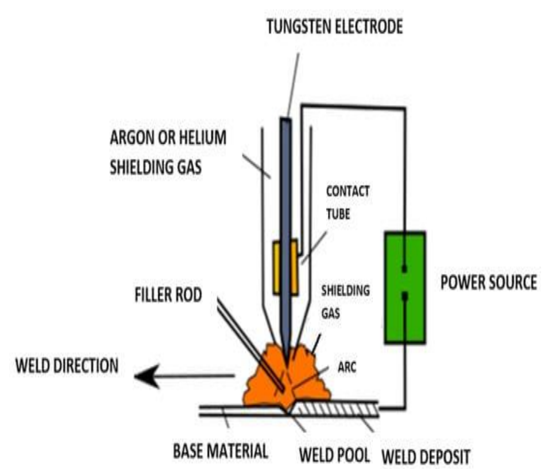

Figure 1: Schematic diagram of tungsten inert gas (TIG) welding incorporated with a filler rod. (Kesse et al., 2020)

Under the correct welding conditions, tungsten electrodes are not consumed during welding (Sharda et al., 2020). However, its process efficiency is low and penetration capability is relatively weak because of its low arc current used. In order to improve the efficiency of heat source, researchers proposed to modify the welding torch and introduce heavier welding current to increase the arc pressure and enhance the penetration capability (Chunyang et al., 2020). Gas is pumped through the nozzle to protect the weld pool against oxidation. The electrode is only intended to maintain the heat supplying arc. The extra metal required for the weld pool is provided by a consumable filler rod fed by the operator (Natrayan et al., 2021). The inert gases are widely used to cover the area welded from the atmosphere (helium, argon, or a combination of helium and argon). For proper welding, filler metal can also be fed manually (Kumar et al., 2022). TIG welding can be used in various positions of parts and is very easy to operate in different situations (Zhang et al., 2019).

1. METHODOLOGY

2.1 Design of Experiment

Design of Experiments (DOE) is a powerful analysis tool for modelling and analysing the influence of multiple control factors on the performance output. DOE refers to planning, designing, and analysing an experiment so that valid and objective conclusions can be drawn effectively and efficiently. If a certain quality feature of a product, the response, is being affected by many variables, the best strategy is then to design an experiment in order to achieve valid, reliable and sound conclusions in an effective, efficient and economical manner. It is important to know that some factors may have strong effects on the response, others may have moderate effects, and some have no effects at all. In manufacturing, experiments are conducted to improve the understanding and knowledge of different engineering processes with the aim of producing high quality products. To achieve this an appropriate combination of the experimental parameters is required. One of the conventional common approaches utilized by many engineers in manufacturing companies is one-variable-at-a-time (OVAT), where the engineer varies one variable at a time keeping all other variables involved in the experiment fixed. This approach required large resources to obtain a limited amount of information about the process. OVAT experiments are often unreliable, time consuming, may not yield the optimal condition and do not address the interaction effect between the process variables. Methods that have statistical bases can replace OVAT experimental approach.

2.2 Central Composite Design (CCD)

The most popular Response Surface Methodology design is CCD. CCD has three groups of design points: (a) two-level factorial or fractional factorial design points, (b) axial points (sometimes called star points) and (c) centre points. CCDs are designed to estimate the coefficients of a quadratic model. All point descriptions will be in terms of coded values of the factors.

2.3 Factors Required for Design of Experiment

For experimentation there some key factors that must be considered so as to achieve reliable and accurate experimental results these are the process parameters. Process parameters are classified into the input parameters and the output parameters. The input parameters considered in this research study is shown in table 1

2.4 Recording of Responses

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 worktable 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, for each experimental runs 5 specimen was used, and the average of the 5 experimental readings were recorded for the 20 runs.

2.5 Response Surface Methodology

RSM is a set of mathematical and statistical techniques that are useful for modelling and predicting the response of interest affected by several input variables with the aim of optimizing this response. RSM are extensively used in situations where there are many input factors that may influence one or more response variables. Response surface methodology (RSM) is a combination of mathematical and statistical models for analysing processes in which a target response is influenced by several variables and the main objective is to optimize this response. It also has an important application in the design, development, and formulation of new products as well as in the improvement of existing product designs. The basic components of response surface methodology include experimental design, regression analysis and optimization algorithms which are used to investigate the empirical relationship. Response Surface Methods (RSM) are used to develop empirical model, commonly called response surface, for the response of a process in terms of the relevant controllable factors. RSM determines the operating conditions that produce the optimum response. Response Surface Methodology allows you to specify and fit a model up to the second order, RSM fits a model and provides the ANOVA and the 'Lack of Fit' test separately when there is more than one response. Contour and Surface plots of each response for pairs of factors are also produced. The aim of the response surface is to help understand the topography of the surface plot using simple maximum or minimum, saddles and ridges 3D diagrams and to find the region with the optimum response using contour plots.

2.6 Artificial Neural Networks

Neural network is data mining tool for finding unknown patterns in databases, a neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects. Knowledge is acquired by the network through a learning process, Interneuron connection strengths known as synaptic weights are used to store the knowledge. An elementary neuron with *R* input is weighted with an appropriate *w*. The sum of the weighted inputs and the bias forms the input to the transfer function *f*. Neurons can use any differentiable transfer function *f* to generate their output. Multilayer networks often use the log-sigmoid transfer function logsig. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig. Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems.

Table 1: input parameters

Parameters	**Unit**	**Symbol**	**Coded valueLow(-1)**	**Coded value High (+1)**
Current	Amp	A	180	240
Gas flow rate	Lit/min	F	16	22
Voltage	Volt	V	18	24

2. RESULTS AND DISCUSSION

In this study, two expert methods were used to analyze the data collected from the experiments performed which are the response surface methodology (RSM) and the artificial neural network (ANN).

3.1 Modelling and Optimization using Response Surface Methodology (RSM)

Response Surface Model is a variation of the simple linear regression, with the incorporation of the second order effects of non-linear relationships. It is a popular optimization technique to determine the best possible combinations of variables to determine a specific response to a phenomenon. RSM is particularly useful to understand the relationship between multiple predictor variables with multiple predicted responses.

The target of the optimization model was to:

i. Maximize weld strength factor.
   The final solution of the optimization process was determining the optimum value of each input variable namely: current (Amp), voltage (V) and gas flow rate (lit/min) that will give us the best weld output results.

To generate the experimental data for the optimization process;

i. Statistical design of experiment (DoE) using the central composite design method (CCD) was done. The design and optimization were executed with the aid of statistical tool. For this particular problem, Design Expert 7.01 was employed.

ii. An experimental design matrix having six (6) centre points(k), six (6) axial points(2n) and eight (8) factorial points(2^n) resulting to 20 experimental runs was generated.

To validate the suitability of the quadratic model in analysing the experimental data, the sequential model sum of squares was calculated for the weld strength factor response as presented in Table 2

The sequential model sum of squares table shows the accumulating improvement in the model fit as terms are added. Based on the calculated sequential model sum of square, the highest order polynomial where the additional terms are significant and the model is not aliased was selected as the best fit. To test how well the quadratic model can explain the underlying variation associated with the experimental data, the lack of fit test was estimated for each of the responses. Model with significant lack of fit cannot be employed for prediction. Results of the computed lack of fit for the weld strength factor is presented in table 3

Table 2: Sequential model sum of square for weld strength factor

Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	**Remark**
Mean vs Total	13.31	1	13.31			
Linear vs Mean	1.337E-003	3	4.457E-004	8.51	0.0015	
2FI vs Linear	2.225E-004	3	7.415E-005	1.58	0.2458	
Quadratic vs 2FI	5.298E-004	3	1.766E-004	47.29	< 0.0001	Suggested
Cubic vs Quadratic	1.693E-005	4	4.231E-006	1.27	0.3922	Aliased
Residual	1.669E-005	5	3.337E-006			

Table 3: Lack of fit test for weld strength factor

Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	**Remark**
Linear	7.820E-004	11	7.109E-005	73.44	0.0004	
2FI	5.596E-004	8	6.994E-005	72.26	0.0005	
Quadratic	2.974E-005	5	5.948E-006	6.14	0.0515	Suggested
Cubic	1.281E-005	1	1.281E-005	13.24	0.0220	Aliased
Pure Error	3.872E-006	4	9.680E-007			

The model statistics computed for weld quality index response based on the model sources is presented in table 4.

To validate the adequacy of the quadratic model based on its ability to maximize the weld strength factor the goodness of fit statistics presented in table 4.

Table 4:Goodness of fit statistics for weld strength factor

Std.	1.933E	R-	0.984

Dev.	-003	Squared	2
Mean	0.84	Adj R-Squared	0.9683
C.V. %	0.23	Pred R-Squared	0.8869
PRESS	2.402E-004	Adeq Precision	29.157

To accept any model, its satisfactoriness must first be checked by an appropriate statistical analysis output.
In order to detect a value or group of values that are not easily detected by the model, the predicted values are plotted against the actual values, for strength factor which is shown in the figure 2. To determine the presence of a possible outlier in the experimental data, the cook's distance plot was generated for the different responses. The cook's distance is a measure of how much the regression would change if the outlier were omitted from the analysis. A point that has a very high distance value relative to the other points may be an outlier and should be investigated. The generated cook's distance for the weld strength factor is presented in Figures 3.

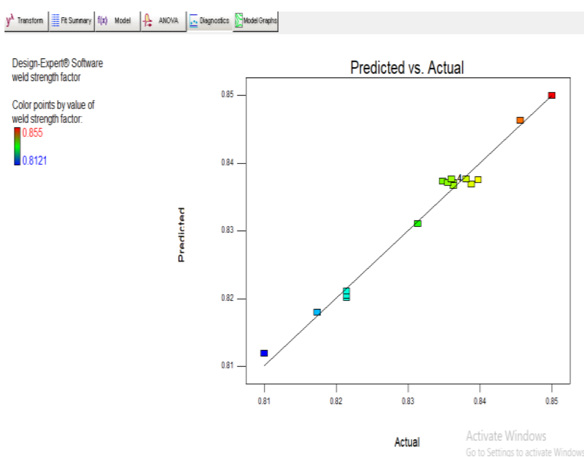

Figure 2: Plot of Predicted Vs Actual for weld strength factor

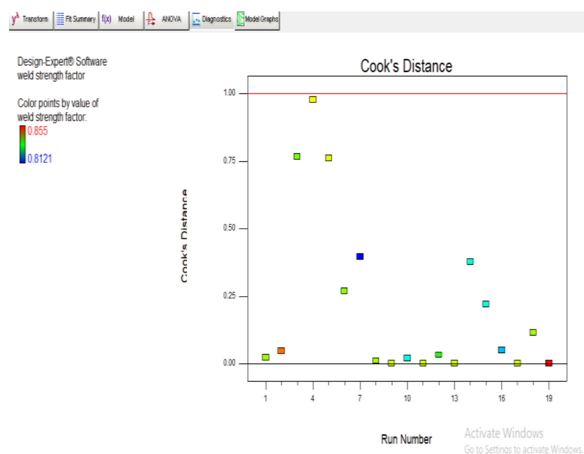

Figure 3: cook's distance plot for weld strength factor

To study the effects of combine input variables on the weld weld strength factor, 3D surfaces plots presented in Figure 4 and Figure 5.

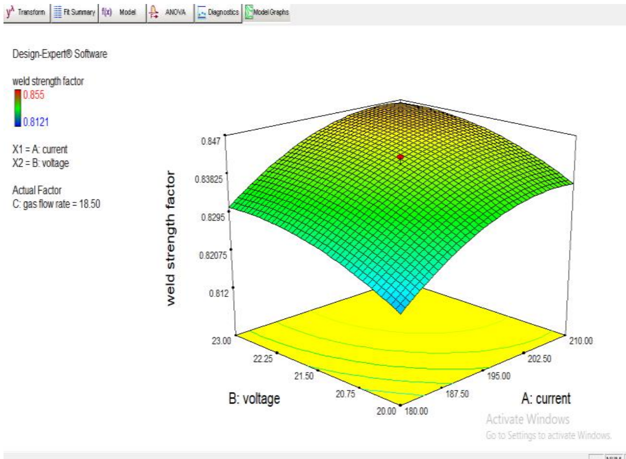

Figure 5: Effect of current and voltage on weld strength factor

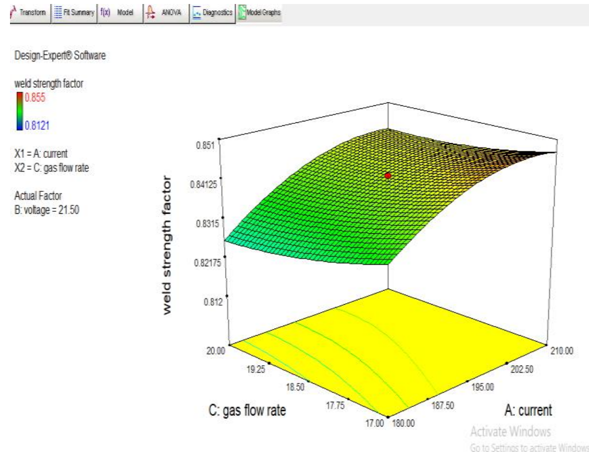

Figure 6: Effect of current and gas flow rate on weld strength factor

3.2 Artificial Neural Network Model

The artificial neural network is a data mining tool that can be used for prediction without having prior knowledge of how the data is collected. This process involves training, learning, testing and validation of the network. For Validation/Test interphase, it is recommended that a set of data be set asi4.de for validation and testing, therefore, that data obtained from this research were divided into three parts with 70% of the experimental sample data, used for training 15% used for validation, while the remaining 15% was used to test the neural network model. This resulted in 20 samples of the entire date used for training while 5 samples each was employed for validation and testing. The ANN network architecture has 3 input ,10 neurons in the hidden layer and 1 neuron in the output layer, the network architecture is shown in figure 7.

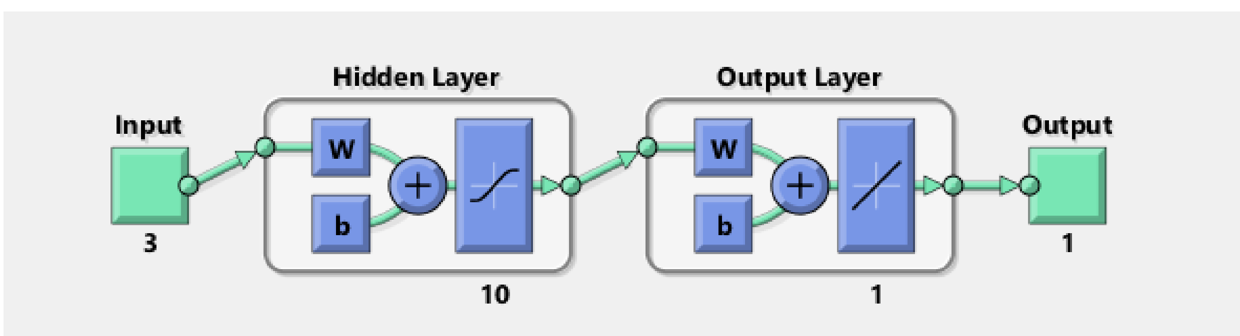

Figure 7: Artificial neural network architecture for predicting weld strength factor response

The Training interphase: from the result summary, it was noticed that the training of the network model provided a correlation having 99.8% with a mean square error of 2.766E-7. The validation of the network model produced a correlation of 94.0% with a mean square error of 1.040E-4. the testing of the network model produced a correlation of 97.7% with mean square error 1.003E-5. Refer to Regression plot of training, validation, and testing for the weld strength factor for clearer understanding. The performance plot was produced to check for network learning and is shown in figure 8. The best validation performance was obtained at epoch 5. In MATLAB software, an epoch can be thought of as a completed iteration of the training procedure of your artificial neural network. Which means, once all the vectors in your training set have been used or gone through your training algorithm, one epoch has been attained. Thus, the "real-time duration" of an epoch is dependent on the training method used. The best prediction for the weld strength factor responses was achieved at epoch 5, although, a total of 5 epochs where used in the iteration process. The gradient function plot is presented in figure 9.

This plot is used to show how much errors had been produced by the neural network model. From the plot, it was noticed that the prediction error made, is indicated by the orange line which is close to -0.0035. a regression plot is produced to check for the coefficient of correlation and the closeness between the network output and the experimental data. The regression plot showing the training, validation and testing of the network output is shown in figure 10.

Figure 10 present the training, validation, and testing plot with correlation coefficient (R) of over 90% which signifies a robust prediction for the Fume Formation Rate. The dotted diagonal line on each plot indicates the line of best fit which indicate a perfect prediction and a correlation of 1.

A time series plot can help to appreciate the graphical difference between the experimental result and the network output which is shown in figure 11.

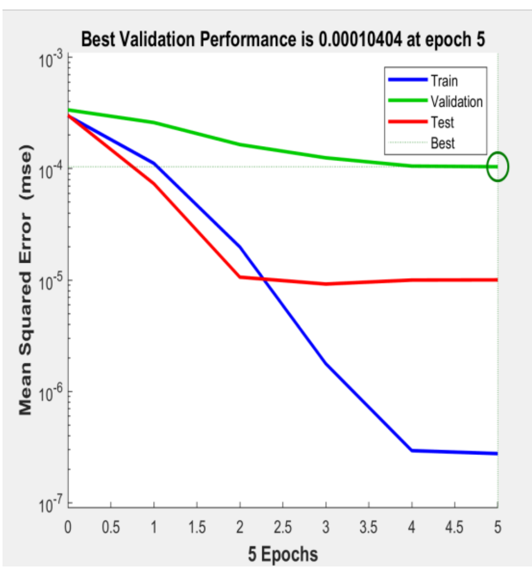

Figure 8: Performance curve for trained network to predicting weld strength factor responses

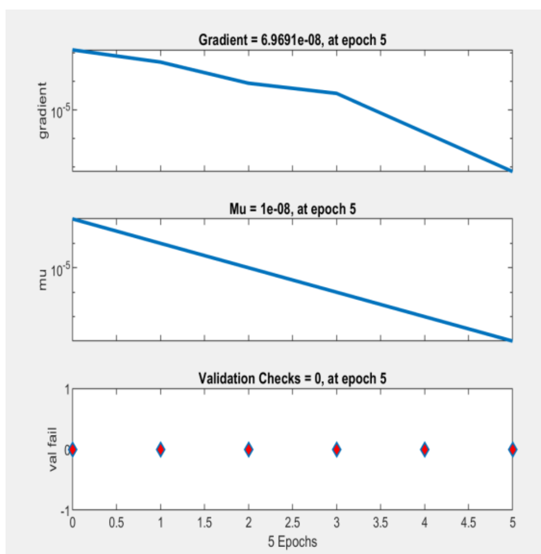

Figure 9: Neural network gradient plot for predicting weld strength factor responses

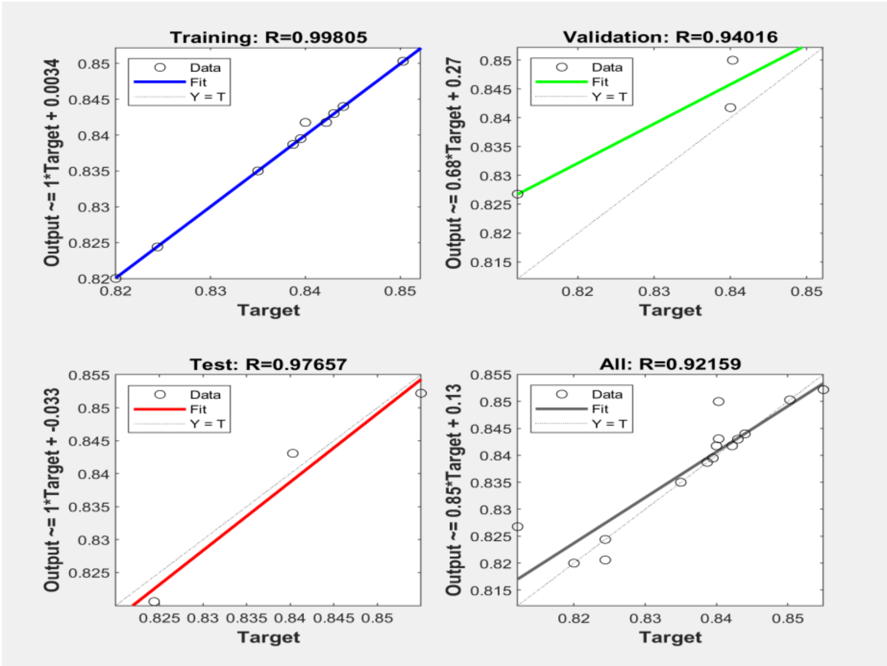

Figure 10: regression plot of training, validation, and testing for weld strength factor responses

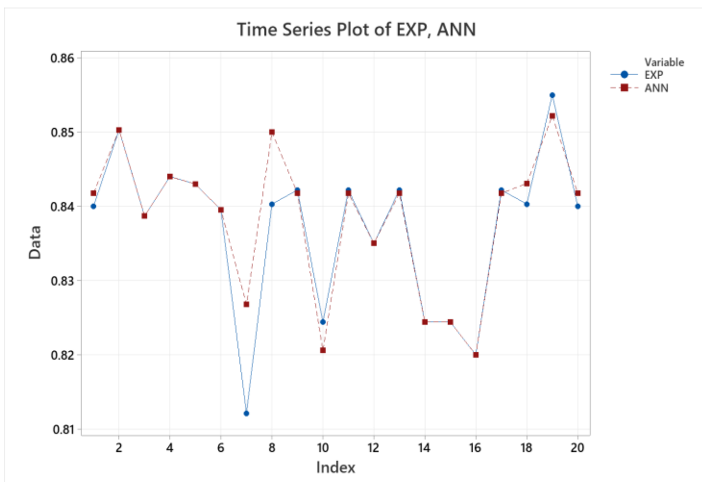

Figure 11: A time series plot of experimental values and network output

The regression equation for the weld strength factor is presented in equation 4.2. It was noticed from the model summary that 0.004224 was the maximum noise produced by the ANN predictive model, showing its robustness.

EXP = - 0.00313 + 1.002 ANN (1)

The model summary statistics for the network shows the strength of the network output. The result is shown in table 5

The analysis of variance for the network output to check for the significance of the network is shown in table 6.

Table 5: ANN Model Summary for weld strength factor

S	R-sq	R-sq(adj)
0.0042247	84.93%	84.10%

Table 6: ANN Analysis of Variance for weld strength factor

Source	DF	SS	MS	F	P
Regression	1	0.0018110	0.0018110	101.47	0.000
Error	18	0.0003213	0.0000178		
Total	19	0.0021323			

A fitted plot for the artificial network output was done to ilustrate the correlation between the experimental and the model developed,which is shown in figure 12.

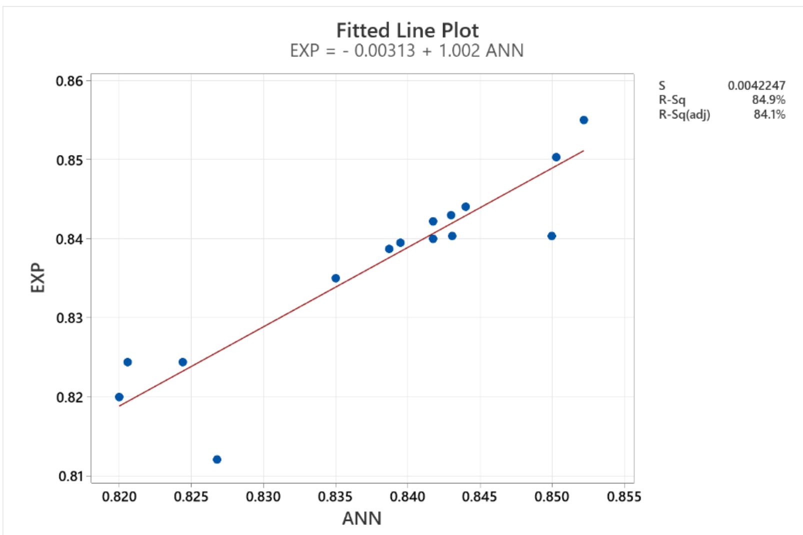

Figure 12: Fitted line plot for the weld strength factor.

3.3 Discussion

In this study, the Response Surface methodology and the artificial neural network methods were used to optimize and predict weld strength factor. The input parameters are current, voltage and gas flow rate, while the response is weld strength factor. The relationship between the process parameters and the weld strength is quadratic, and shows a strong correlation between the current, voltage and weld strength factor formed with a coefficient of correlation value of 0.9842. The variance inflation factor (VIF) was 1.00 which indicates that the model is significant because a (VIF) greater than 10.00 is a cause for alarm. The ANOVA table shows that the model is significant and possess a very good fit with a P -value of < 0.0001. To validate the significance and adequacy of the model based on its ability to optimize the weld strength factor, the goodness of fit statistics gave a Coefficient of determination R^2 of 0.9842 indicating how well the model can predict the values of the selected variables that will maximize the weld strength factor. The model has a noise to signal ratio of 29.157, which is greater than 4 is desirable and indicates an adequate signal. Finally, numerical optimization was performed to ascertain the desirability of the overall model. In the numerical optimization phase, we ask design expert to maximize the weld strength. From the results, it was seen that current (210.00amp), voltage (22.66volt) and gas flow rate (20.00litre/min) will produce weld with weld strength factor of 0.842156. This solution was selected by design expert as the optimal solution having a desirability value of 0.880. The study reveals the successful use of artificial neural networks in predicting the weld strength for tungsten inert gas welding of mild steel plates. The mean square error was used to measure the performance of the network in each run. The mean square performance index for the network is a quadratic function. The input data are randomly divided into three sets. 70% are used to train the network, 15% are used to validate the network performance and 15% are used for the test. For the training interphase the network provided a correlation value of 99.8% with a mean square error of 2.766E-7. The validation of the network model produced a correlation value of 94.0% with a mean square error of 1.040E-4. the testing of the network model produced a correlation of 97.7% with mean square error 1.003E-5. The performance plot showed that the model developed was learning, which is expected of a very good network. Finally, the artificial network model produced predicted values for the weld strength of which the predicted values and the experimental values of the responses, closely fit and are in reasonable agreement with a high coefficient of correlation.

4. CONCLUSION

The integrity of a Weld is determined by the quality index and strength of the weld bead. The higher the strength and factor of safety of a weld, the higher the integrity and reliability of the weld. In this study the response, surface method and the artificial neural network model were both employed to predict and optimize these output parameters mentioned in this study. From the results obtained the response surface methodology is selected as the better predictive model over the Artificial Neural Network because it has a lower mean square error value. A mathematical model was developed using the Response Surface Methodology and the Artificial Neural Networks to optimize and predict the weld strength factor in order to enhance service life and integrity of welded joints. The models strength, accuracy and efficiency have been tested and validated. Results obtained in this study showed that current has a strong influence on the weld strength factor that means to achieve a higher weld strength factor the current can be used to control it. The variance inflation factor has a value of 1 for the independent term and 1.04 for the combined and quadratic terms of the input factors. The results revealed that the improved second order method of gradient also known as Levenberg Marquardt Back Propagation training algorithm was the best learning rule and was adopted in designing the network architecture. It was observed that training algorithm had 10 hidden neurons in the input layer and output layer.

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